Overpriced Winners*

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Abstract

A strong increase in a firm's market price over the past year is generally associated with higher future abnormal returns, consistent with the momentum anomaly. However, for a small set of firms for which arbitrage is limited, high past returns forecast strongly negative future abnormal returns. We propose a dynamic model in which increased unwarranted optimism by a set of speculators leads to dynamic mispricing effects. Consistent with this model, we show a set of firms with high past returns, low institutional ownership, and high recent changes in short interest earns persistently low returns going forward. A strategy that goes short the overpriced winners and long other winners generates a Sharpe-ratio of 1.08; its returns cannot be explained by commonly used risk-factors.

Keywords: short-selling, short-sale constraints, divergence-of-opinion, momentum, limits of arbitrage, market efficiency, bubbles

JEL-Classification: G12, G14

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1 Introduction

Figure 1 plots the average cumulative log excess returns to four portfolios in the 60 months after formation. The red line in the plot is the value-weighted market-portfolio. Not surprisingly, the cumulative return of the market increases linearly with the holding period by the average monthly excess return of the market over this period: 0.64%/month. Also not surprising are the cumulative average log returns for the portfolios labeled "Winners" and "Losers," which at the start of month t, invest in a value-weighted portfolio of the 20% of US common stocks with the highest and lowest cumulative returns from month t-12 through month t-2.[1] Their performance is consistent with the literature on momentum: over about the next year, the past winners outperform the past losers by substantial margin.

INSERT Figure 1 HERE

The new result in Figure 1, and the focus of this paper, is the cumulative-log-excess-return for the "Constrained Winners" portfolio. The firms in this value-weighted portfolio are also past winners, but here we select the subset of past winners for which the limits to arbitrage are strong. Specifically, these are past winners which are in the bottom 20% in terms of institutional ownership, and in the top 20% in terms of the increase in short-interest over the past year.

As a complement to Figure 1, Figure 2 plots the time series of cumulative returns to the past winner, past loser, and the constrained past-winner portfolios, hedged with respect to the three Fama and French (1993) factors over the sample-period.[2] Again we see that the hedged past-winner and past-loser portfolios earn strong positive and negative average abnormal returns respectively, consistent with the momentum effect documented by Jegadeesh and Titman (1993).

INSERT Figure 2 HERE

Also consistent with the evidence in Figure 1, the average excess return of the hedged constrained past-winners in the month after formation is -2.47%. An investment of $1000 in this dynamic hedged portfolio on June 1st 1989 would have been worth $0.38 at the end of December 2014, a striking loss of value, particularly given that these are high momentum stocks. What is responsible for the strikingly different performance of the constrained and unconstrained winners? We argue here that the shocks that caused these stocks to become past-winners are inherently different. For the majority of the *unconstrained* past-winner firms, the

[1] This is consistent with the procedure used in Carhart (1997) and the formation of the momentum portfolio on Kenneth French's data library. See the detailed description for the monthly momentum factor at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor.html.

[2] Specifically, we calculate the returns to the past-winners for each sample month. We then run a full-sample regression of the past-winner returns on Mkt-RF, SMB, and HML. Then, using the full-sample regression coefficients, we subtract the returns of the zero-investment hedge-portfolio $[b_{Mkt}*(R_{Mkt}-R_{f,t})+b_{SMB}*SMB_t+ b_{HML}*HML_t]$ from the past-winner returns to generate the hedged-past winner returns. The factor return data comes from Kenneth French's data library.

high past returns generally reflect positive fundamental value shocks: these stocks likely rose in price as good news was released about the firms' ability to generate future cash flows. For reasons explored in the behavioral finance literature, there is underreaction or delayed-overreaction to these fundamental shocks that leads to the momentum effect that we see in both the "past winner" and "past loser" graph on the preceding page (see, e.g., Barberis, Shleifer, and Vishny, 1998, Daniel, Hirshleifer, and Subrahmanyam, 1998, Hong and Stein, 1999).

However, for the constrained winners, we argue that a possible source of the price rise was that only a subset of investors revised upward their valuation of the firm in response to what we will label a "sentiment" or "disagreement" shock. For an unconstrained firm, the price would not move appreciably in response to such a shock; the subset of now-optimistic investors affected by the sentiment shock would demand more shares, but in response the arbitrageurs (whose valuation of the firm was unaffected by this shock) would short the shares demanded by the optimists. However, for a constrained stock, where it is difficult for the arbitrageurs to borrow and short the stock, competition between the optimistic investors will lead to a strong, unwarranted price rise for the stock. As this optimism wanes in coming months, the constrained winners' prices fall, leading to the negative returns seen in Figures 1 and 2.

We note that the shock that we describe and model here can be thought of either as an individual-firm sentiment shock (see, e.g., Stambaugh, Yu, and Yuan, 2012), or as a shock to disagreement about the firm's prospects (see, e.g., Diether, Malloy, and Scherbina, 2002), because following the shock, the optimists and the arbitrageurs disagree about the firm valuation. We capture this isomorphism in the models we present.

Our baseline model is in the spirit of Miller (1977). There is a set of agents ("speculators") who disagree about the fundamental value of each firm. The prices at which shares change hands in the market reflect the distribution of agents' valuations, and new information can cause the distribution of valuations to change. Conceptually, we can think of new information as affecting the mean and the variance of the distribution of valuations, and label the variance as disagreement.

In our simplified setting, for unconstrained firms where the cost of locating shares to borrow is zero, a shock to disagreement or optimism has no effect on the price. Here, such shocks result in trading volume – the agents who become more optimistic buy shares from those who are more pessimistic – but the market-clearing price remains constant. However, for firms where short selling is constrained (i.e., where it is costly to find shares to borrow) the more pessimistic agents choose not to short because of the high cost of finding shares to borrow. Thus, the market-clearing price no longer reflects the valuations of these newly "sidelined" pessimists, and moves upward. Hence, if we see that a constrained firm has experienced a large price rise over the last year, it is likely that disagreement for this firm has increased, which further implies that this firm is likely to earn low returns as the disagreement is resolved.

The mechanics of the model become clearest in light of evidence on the dynamics of beliefs. We will argue that the dynamics of beliefs can be approximately thought of as a two-state Markov process, as we are able to summarize the dynamics of beliefs with the two Markov transition probabilities: what we observe is that the probability of a stock transitioning from low- to high-disagreement is small, and the probability of a stock transitioning from high- to low-disagreement is large.

INSERT Figure 3 HERE

Figure 3 illustrates the actual dynamics of one measure of disagreement: the dispersion in analysts' forecasts of future earnings taken from the IBES summary database, an analysis we discuss in detail in Section 5 of this paper. The idea here is that analyst forecast dispersion for a given stock is a proxy for disagreement among beliefs of the agents trading this stock (see, e.g., Diether, Malloy, and Scherbina, 2002). To construct Figure 3, we sort firms into decile portfolios based on the change in forecast dispersion over the period from year t-1 to t, and then plot the level of the forecast dispersion from year t-1 until year t+5 for these decile portfolios.

What Figure 3 shows is that there are relatively few high dispersion firms – only deciles 1 and 10 ever exhibit average dispersion that exceeds 0.2 – and that those firms that experience a positive shock to dispersion revert to a low level within roughly 5 years.

In our model, changes in disagreement result in commensurate changes in the price levels for firms which are short-sale constrained. Thus, for constrained firms, *forecastable* changes in disagreement should lead to forecastable returns.[3] Figure 3 makes it clear that constrained, high-disagreement firms should earn low returns over the next several years, as the disagreement about these firms is resolved. In principle, if it were possible to identify constrained firms for which disagreement was likely to increase, one could earn high returns by buying these firms.[4] However, while it is straightforward to identify firms where disagreement will fall, positive shocks to disagreement are difficult to forecast. We cannot build a portfolio which earns positive abnormal returns from buying firms which experience disagreement increases, because we cannot forecast which firms these will be. However, given the high likelihood of transitioning from high- to low-disagreement, we know that a portfolio of constrained firms which are high-disagreement today will, on average, earn low returns as disagreement about these firms is resolved in the future.

Our dynamic model generates implications consistent with our empirical findings. In our multi-period setting, an optimist and a pessimist trade an asset that pays a liquidating dividend at time T. The liquidating dividend is the sum of fundamental shocks that are revealed to the agents each period. The optimists

[3] Note that, in our model, the overconfident optimists who effectively set the security price of constrained firms do not anticipate that they will revise their expectations downward in the future as disagreement is resolved.

[4] This is assuming that the disagreement shock was not anticipated by the market. Scheinkman and Xiong (2003) present a model where disagreement shocks are anticipated by the market.

and pessimists initially hold divergent and biased beliefs about the mean of the distribution from which these shocks are drawn. Using Bayes' rule, they update their beliefs as they observe the realizations of the fundamental shocks each period. As a consequence, over time their beliefs converge towards the rational expectation belief, and prices converge towards the rational expectation price, mirroring the decay of disagreement in ΔEFD-portfolio 10 in Figure 3 and the price pattern of constrained winners in Figure 1.

When we take the predictions of our model to the data, we are able to identify short-sale constrained high disagreement stocks. This portfolio has a small number of firms—consistent with the fact that short-sale constraints in the US market are rare (see D'Avolio, 2002, Geczy, Musto, and Reed, 2002), and with the low frequency of big positive disagreement shocks. On average, our constrained past-winner portfolio contains 16 firms. Despite this, a long-short portfolio that buys a broad portfolio of past-winners and shorts the constrained past-winners ("Betting Against Winners") earns a Sharpe-ratio of 1.08 and a Fama-French three-factor-α of 2.71%/month (t-stat=5.77) over the 1989-2014 sample period.[5] In addition, we show that these large returns cannot be explained by other factors proposed in the finance literature.

We provide further empirical analyses that strengthen the case that the constrained winners are actually overpriced because of disagreement shocks. First, if disagreement is originally causing overpricing, then negative returns should be especially realized around earning announcements when disagreement is likely to be resolved (Berkman, Dimitrov, Jain, Koch, and Tice, 2009). We find that 67% of the negative returns of constrained winners in the first three months are earned in the three days after earnings announcements. Second, managers who believe their own equity to be overvalued, and act in the interest of existing shareholders, should issue equity (see, among others, Baker and Wurgler, 2002). We find abnormal equity issuance activity for constrained winners relative to other winners.

In summary, our empirical strategy identifies a particular set of individual stocks for which a run-up in prices leads to strong negative returns going forward. We present evidence consistent with the idea that the run-up in prices was generated by excessive optimism on the part of a set of investors. Interestingly, our evidence is consistent with the definition of a "bubble" provided by Fama (2014), who states that "[Policymakers and some academics] define a 'bubble' as an irrational strong price increase that implies a predictable strong decline" (p. 1475) and goes on to argue that "the available research provides no reliable evidence that price declines are ever predictable." At least at the individual stock level, our evidence is consistent with the existence of such "bubbles."[6]

[5] Note, of course, that this return would likely not have been achievable in practice, as it is likely that the constrained winners were costly to borrow for the purposes of short-selling,

[6] See Greenwood, Shleifer, and You (2016) for evidence at the industry level.

2 Related Literature

Our paper is related to three connected strands of literature: The literature on the institutional details of the equity lending market, the literature on market mispricing caused by a combination of biased beliefs and limits of arbitrage, and the literature on disagreement and asset prices.

D'Avolio (2002), Geczy, Musto, and Reed (2002), Kolasinski, Reed, and Ringgenberg (2013) and Kaplan, Moskowitz, and Sensoy (2013) investigate the lending market in great detail using proprietary data. Overall, these papers find that all but a few percent of common stocks can be borrowed at low cost for short selling purposes. Their descriptions of the loan market match key features of our model setup: The demand-schedule for borrowing stocks is downward sloping. Loan supply is represented by long-holdings of investors who are willing and also able to lend out their securities. Borrowing demand shifts lead only to rising loan fees if shorting demand is already high, but not for low levels of shorting demand.

The theoretical literature on limits of arbitrage has identified numerous forces that inhibit arbitrage and thus enable mispricing to occur in financial markets. Shleifer and Vishny (1997) show how biased beliefs can have an impact on asset prices in the presence of noise trader risk. Abreu and Brunnermeier (2002, 2003) introduce synchronization risk to explain why prices can disconnect with fundamentals. Gromb and Vayanos (2010) survey and summarize a number of limits of arbitrage.

The empirical challenge in identifying asset pricing bubbles has been the lack of observability of the fundamental value which leads to the joint hypothesis problem (Fama, 1970). Recent work by Greenwood, Shleifer, and You (2016) shows that sharp price increases of industries, along with certain characteristics of this run-up, help to forecast the probability of crashes and thereby help to identify and to time a bubble. Our work adds to this strand of literature, as we show, on an individual stock basis, that price run-ups can be used to forecast low future returns when paired with indications of limits of arbitrage. Consistent with this, using institutional ownership as a proxy for low lending supply, recent papers show that short-sale constraints are positively related to the profitability of quantitative strategies designed to exploit mispricing (see, e.g., Nagel, 2005, Hirshleifer, Teoh, and Yu, 2011, Stambaugh, Yu, and Yuan, 2012, Drechsler and Drechsler, 2016). In light of the literature on mispricing and limits of arbitrage, our empirical approach is unique in the sense that it can be interpreted as a methodology to identify bubbles on the individual stock level.

The third line of literature focuses on disagreement and short-sale constraints based on the idea of Miller (1977). Boehme, Danielsen, and Sorescu (2006) emphasize the importance of both conditions being met simultaneously and provide evidence that either condition alone is not sufficient to document overpricing. Earlier studies have approached the Miller idea by utilizing short interest to proxy for short-sale constraints or costs, including Figlewski (1981), Asquith and Meulbroek (1996), Desai, Ramesh, Thiagarajan, and Balachandran (2002), or, alternatively, using data on loan fees, such as Jones and Lamont (2002) and Blocher, Reed, and Van Wesep (2013). Asquith, Pathak, and Ritter (2005) consider institutional ownership to proxy for supply and short-interest for demand. In their sample from 1988-2002 they find underperformance of supposedly constrained stocks on an equal-weight basis, but no significant results when using value-weighting. They conclude that for the vast majority of stocks short-sale constraints are unlikely. Using proprietary loan-fee and -quantity data in a limited sample from 1999-2003, Cohen, Diether, and Malloy (2007) also look at supply and demand shifts. They find that demand shocks contain predictive power for future returns on an equal-weight basis, while shocks to supply have no significant effect. The latter result is confirmed by a natural experiment in Kaplan, Moskowitz, and Sensoy (2013), who exogenously shock the loan supply of a subset of stocks and find no pricing implications.

Focusing on the divergence-of-opinion part of Miller's argument, Diether, Malloy, and Scherbina (2002) and Danielsen and Sorescu (2001) show that firms for which the dispersion of analysts' forecasts of future earnings is high earn lower future stock returns. Berkman, Dimitrov, Jain, Koch, and Tice (2009) use different proxies for divergence-of-opinion, such as earnings and return volatility, forecast dispersion and turnover, and find strong negative returns around earnings announcements, which they argue are consistent with the announcement resolving uncertainty or disagreement. The effect is enhanced in the presence of low institutional ownership, which is arguably related to short-sale constraints.

Nagel (2005) examines the share lending market, and specifically the effect of institutional ownership on documented anomalies. He argues that institutional ownership is a proxy for lending supply and consequently ease of short-selling. Moreover, he shows that the predictive power of forecast dispersion, turnover and volatility—all proxies for disagreement—are stronger when institutional ownership is low. Nagel (2005) concludes that his findings are consistent with the idea that short-sale constraints prevent the incorporation of pessimistic views into market prices. Drechsler and Drechsler (2016) provide further evidence that anomaly returns are concentrated in stocks that are expensive to short.[7] They relate this to the risk of bearing underdiversified positions specific to short-sellers. In a similar vein, Engelberg, Reed, and Ringgenberg (2016) relate loan fee uncertainty and recall risk to price inefficiencies.

Our model combines key features of all of these literature strands in one parsimonious model, makes concrete predictions concerning empirically observable quantities, and links the dynamics of disagreement to the price dynamics. The combination of a firm's past return with a change in short-interest constitutes a unique and innovative proxy for mispricing caused by biased beliefs or divergence-of-opinion that can be used

[7] In contrast, Israel and Moskowitz (2013) provide evidence that momentum, value and size are robust on the long side and thus do not overly rely on short-selling.

in other contexts. An advantage of our alternative proxy over analysts' forecast dispersion, a frequently used proxy of divergence-of-opinion, is better data availability. Analysts' forecast dispersion is only available for about 50% of the stocks in the US cross-section, but the combination of short interest with past performance is available for 78% – a 56% increase in the number of firms.[8] Also, forecast dispersion is typically not available for small stocks with low institutional holdings, where dynamic mispricing effects are presumably most likely.

Our model is related to others that formalize the idea that divergence-of-opinion combined with short-sale constraints influences asset prices (see, e.g., Harrison and Kreps, 1978, Diamond and Verrecchia, 1987, Chen, Hong, and Stein, 2002, Hong and Stein, 2003, Scheinkman and Xiong, 2003, Gallmeyer and Hollifield, 2007, Ang, Shtauber, and Tetlock, 2013, Hong and Sraer, 2016). Duffie, Gârleanu, and Pedersen (2002) explicitly model the search and matching process on the lending market. Our approach is to model the lending market as a market where supply and demand determine equilibrium quantities in the same way as on the stock or a standard goods market. This approximation of the complex search process for borrowing stocks in the real world allows us to endogenize lending costs in a simple way. Our approach keeps the model as tractable as possible, while still capturing the intertwined supply and demand mechanism on the lending and stock market that we are interested in and that is at the heart of our empirical analysis.

Our paper shares this parsimonious modeling approach with a series of mostly recent papers. Blocher, Reed, and Van Wesep (2013) simultaneously model the stock and lending market. Positive shorting costs only arise if demand for borrowing stocks exceeds free lending supply - similar as in our static model. Reed, Saffi, and Van Wesep (2016) and Weitzner (2016) present extensions of the model to study a disagreement-based explanation of the conglomerate discount and the term structure of equity shorting costs, respectively. Duffie (1996) models similar effects of the Treasury repo market on Treasury prices.

There are two main differences between this literature and our paper. Most importantly, our model is dynamic and we explicitly model the dynamics of beliefs. We base this on an empirical analysis of analysts' forecast dispersion. By doing so, we are able to explain why increases in excessive optimism and disagreement forecast negative returns, while decreases have almost no predictive power. Second, our paper points out a previously overlooked connection between the literature on disagreement and momentum. High returns together with a change in short interest can be interpreted as an indication of a positive shock in excessive optimism or disagreement. As these stocks underperform going forward, the resulting disagreement-based pattern of overpricing and subsequent reversals is very different from the overpricing-and-reversal-pattern predicted by models that aim to provide a behavioral explanation of the momentum effect (see Barberis,

[8] After applying some additional data cleaning to the short interest data, coverage increases to 86%. Details can be found in Appendix F.

Shleifer, and Vishny, 1998, Daniel, Hirshleifer, and Subrahmanyam, 1998, Hong and Stein, 1999). Our model suggests that the key to identifying these stocks empirically is a change in short interest. Only those stocks with low lending supply that experience an increase in prices and short interest at the same time are stocks exposed to the disagreement-based mechanism of overpricing and reversals.

Empirically, we provide robust negative long-term return predictability from high short-interest with value-weighted portfolios. Existing papers, such as Asquith and Meulbroek (1996), Dechow, Hutton, Meulbroek, and Sloan (2001), Desai, Ramesh, Thiagarajan, and Balachandran (2002), Asquith, Pathak, and Ritter (2005), Boehmer, Jones, and Zhang (2008), Diether, Lee, and Werner (2009), or Drechsler and Drechsler (2016), generally reach significantly abnormal returns based on short-sale activity with equal weighting or for short-term horizons.

On a final note, momentum returns have been weak over the last 10-15 years, as documented in Figure 9 (also see, e.g., Daniel and Moskowitz, 2016). In contrast, the return patterns we document here remain intact over the full sample period. Collectively, our theoretical and empirical findings suggest that short-sale constraints can lead to large individual firm price 'bubbles' where prices are detached from fundamentals for a substantial amount of time.

3 Data

We collect monthly return and market capitalization data from the Center for Research in Security Prices (CRSP). Our sample consists of all NYSE, AMEX and NASDAQ stocks with positive market capitalization and without any additional filters.[9] For some analyses, we calculate idiosyncratic volatility and historical CAPM betas. These are based on daily CRSP returns. The former is calculated as the residual standard deviation of a monthly regression of daily firm-excess returns on the three Fama and French (1993) factors, following Ang, Hodrick, Xing, and Zhang (2006). Historical betas are calculated in a CAPM-regression with daily data as in Frazzini and Pedersen (2014), i.e., over a 5-year window for correlations, while using a 1-year window for variances. Book-equity data is from Compustat. To calculate the book-to-market ratio, we divide it by the sum of market equity of all equity securities (PERMNOs) associated with the company (PERMCO) in December.

Institutional ownership (IO) comes from Thomson-Reuters Institutional 13-F filings. We divide it by the number of shares outstanding from CRSP to get the institutional ownership ratio (IOR). Since they are reported quarterly, we use reported IO in month t for the following three months t+1 to t+3, to be sure it

[9] Our results are robust to excluding micro cap (lowest two decile) stocks. Since we use value-weighted portfolios and the portfolio of interest does not comprise the smallest stocks, it makes virtually no difference.

is in the investors' information set at portfolio formation. Following Nagel (2005), stocks that are in CRSP but are missing IO data are assigned zero institutional ownership.[10]

Our short-interest data is collected from two sources: Short interest data prior to June 2003 data come directly from the NYSE, AMEX and NASDAQ. Our short-interest data after June 2003 is from Compustat. This methodology is guided by Curtis and Fargher (2014), Ben-David, Drake, and Roulstone (2015), Hwang and Liu (2014), and, Hanson and Sunderam (2014). The reason why exchange data is given priority over Compustat data before mid-2003 is that the latter's coverage is generally low and virtually non-existent for NASDAQ stocks before that date. In order to have data from one source and thus make it more comparable within any given month, we give preference to the exchange data pre-June-2003.[11] Coverage starts in June 1988 and constitutes the bottleneck for all analyses. We divide by the number of shares outstanding from CRSP to get the short-interest-ratio *SIR*.[12]

Analyst-forecasts of fiscal-year-end earnings are from Institutional Broker's Estimate System (IBES). We use the summary file unadjusted for stock splits, to avoid the bias induced by ex-post split adjustment, as pointed out by Diether, Malloy, and Scherbina (2002). Earnings-forecast-dispersion (EFD) is the standard-deviation of forecasts normalized by the absolute value of its mean. We truncate values at the 99^{th} percentile, as very low mean forecasts lead to extremely large values that bias results. Values with mean forecasts of zero are excluded.

One proxy that we use for short-sale costs is the put-call-parity violation, as argued in Ofek, Richardson, and Whitelaw (2004). We measure it by the volatility spread, i.e., the open-interest-weighted average difference of implied volatilities of matched call/put option pairs, as calculated in Cremers and Weinbaum (2010). Data are from option prices at month-end from Option Metrics.

4 Model

We begin by laying out a static model that captures the most relevant features. This model has a market for a stock with divergence-of-opinion, a restriction that shares must be borrowed to be sold short, and a lending market. We derive an equilibrium in which both markets clear. Later we extend this basic model to a dynamic (three-period) setting, which allows us to study the dynamics of the quantities of interest and derive empirical implications.

[10] We identify some firms with implausible jumps in institutional ownership and apply a simple procedure to fix this in Appendix F.

[11] There are two exceptions: Exchange data from NYSE before September 1991 and AMEX data before 1995 are not available and thus replaced with Compustat data. Furthermore, data from NASDAQ in February and July 1990 is missing, as pointed out in, e.g., Hanson and Sunderam (2014), and we consequently completely eliminate these months from all analyses.

[12] We apply additional procedures to better match short interest data with CRSP. This increases the number of firm-month observations, reduces noise and strengthens all results. Details can be found in Appendix F.

4.1 Overview

Our basic model is an extension of the Miller (1977) setting. There are several sets of agents: Passive investors' demand for shares is independent of price, and a subset of these investors lend out the shares they hold in a competitive lending market. We can think of these passive investors as large index-funds with organized lending programs. As long as the shares the passive investors supply to the market exceed the shares demanded for the purpose of shorting, the cost of borrowing shares is zero.

Second, there is a set of speculators who take positions on these securities based on perceived mispricing. These speculators have, on average, correct valuations of the securities, but they disagree: a representative optimist is overly optimistic, and a representative pessimist is overly pessimistic. However, we show later, that the pessimist can also be an arbitrageur who is correct in his assessment of fundamental value. When the cost of borrowing shares is zero, the optimist purchases shares, and the pessimist/arbitrageur sells short, and the price reflects the average valuation – that is the security is correctly priced. However, particularly if there are few institutions lending out shares, the short seller (or her broker) will be required to search for shares to borrow. Search is costly, and this cost is taken into account by the (optimizing) pessimistic speculators. In equilibrium, the most pessimistic investors pay the borrowing costs and short sell a smaller amount than they would if the cost of borrowing were zero, leading to an equilibrium price above the security's fundamental value.

4.2 Static Model Setup

Our basic model has a single period. There is a single stock with one share outstanding, which has a final payoff of $V + \epsilon$, where $\epsilon \sim \mathcal{N}\left(0, \sigma^2\right)$. There are two sets of agents: first, there is a mass of passive investors who demand one share of the stock (i.e., the total outstanding supply) regardless of the share price. Note that this means that the other agents – the speculators – must hold zero shares in aggregate. In our basic setting, there are two representative speculators with divergent beliefs about the payoff of the stock: The optimistic speculator believes that the expected final payoff of the stock is $\theta_O = V(1 + \alpha)$, while the pessimistic speculator believes that the final payoff is equal to $\theta_P = V(1 - \alpha)$, with $\alpha > 0$. α is a measure of the speculators' divergence-of-opinion. The speculators agree on the variance of the stock's payoff. There are no trading costs, with the exception that, if an agent goes short, that agent must pay a per-share shorting cost of c.

In this setting, speculators are always right on average, in that the average of the speculators' expected payoffs is equal to the rationally expected payoff, but one speculator is an "optimist" and the other one a "pessimist." This disagreement is implicitly linked with overconfidence, in that the speculators know that the other speculator has a different belief, but each chooses to believe that her view is correct, and the other agent's view is mistaken. This could be motivated by agents receiving private signals, and a (mistaken) belief that their signal is more precise than other's signal (see, e.g., the discussion of overconfidence and disagreement in Daniel and Hirshleifer, 2015). Speculators have CARA preferences with risk aversion coefficient γ.

4.3 The Stock Market

In this CARA-normal setting, the speculators' beliefs and preferences translate directly into demand and supply.[13] In equilibrium, the aggregate demand from the two sets of speculators must equal the aggregate remaining supply of zero (i.e., $x_O + x_P = 0$, meaning the optimist will necessarily go long and the pessimist will go short an equal and opposite amount). Specifically, the optimist chooses his demand x_O so as to maximize his expected utility $u(x_O) = x_O(\theta_O - p) - \frac{\gamma}{2}x_O^2\sigma^2$. This gives a demand for the optimists of:

$$x_O = \frac{(\theta_O - p)}{\gamma\sigma^2} \tag{1}$$

x_O equals the total demand on the stock market $S^d(p)$ in our baseline specification.

The situation is different for the pessimist, who will generally short sell the stock. To short sell she is first required to locate and borrow the shares that she sells. When shares are hard to borrow, the equilibrium cost of borrowing the shares, c, rises above zero. We will model the stock lending market separately in the next subsection.

The pessimist solves the same problem as the optimist, except that the she will only short sell if she believes that the expected profit per share from shorting, $p - \theta_P$, is greater than the cost c, i.e., if $p > \theta_P + c$. In this case, the number of shares sold short $(S^s(p))$ is equal to minus one times the agent's demand and given by:

$$-x_P = \frac{p - (\theta_P + c)}{\gamma\sigma^2} \tag{2}$$

This is different from Equation (1) only because of the search cost c. The stock market clears if aggregate total speculator demand equals the total supply of zero (i.e., if $x_O + x_P = 0$). This gives us the market clearing condition for the stock market as:

$$p = V + \frac{c}{2} \tag{3}$$

[13] Thereby we implicitly assume that prospective lending fees are not considered as a motive for holding stock, as is proposed, e.g., by Duffie, Gârleanu, and Pedersen (2002).

Corollary 1: *The mispricing will always equal one half of the costs of short-selling one unit of stock, i.e.,* $\frac{c}{2}$.

Figure 4 Panel A illustrates the supply and demand functions as well as market clearing in the stock market.

INSERT Figure 4 HERE

4.4 The Lending Market

Consistent with US institutional restrictions, shares of stock must be borrowed before they can be sold short, and can only be borrowed for the purpose of short selling. Thus, the number of shares borrowed is at all times equal to the number of shares sold short. To equilibrate supply and demand of shares, there is a price/cost of borrowing per share of c. In order to short-sell stock, pessimists borrow shares on the lending market. Given our model specification, the only borrower of shares is the representative pessimistic speculator who wants to short. The number of shares she borrows in the lending market, $L^d(c)$, is necessarily the same as the number of shares she shorts, as given in Equation (2):

$$L^d(p,c) = \frac{p - \theta_p - c}{\gamma\sigma^2} \tag{4}$$

Note that, given the institutional features discussed above, the equilibrium borrowing L^* will also be the short interest for this stock.

We model the supply of shares to the lending market as a function of the unit borrowing cost c as:

$$L^s(c) = \lambda + \frac{1}{\tau}c \tag{5}$$

The intuition for this specification is as follows: first, a fraction λ of the passive investors are willing to lend out their shares in the lending market. We can think of this as institutional lending supply, coming from index funds, pension funds, etc., that have set up a stock lending program. As long as the demand to borrow shares is less than this institutional supply, the institutions compete in the lending market, driving the cost of borrowing to zero. However, after the institutional lending supply is exhausted, finding additional shares to borrow requires the payment of search costs. These search costs increase the more shares are demanded.

Rearranging Equation (5) to the costs of borrowing one share of stock, gives the short-sale cost-function

$$c(L) = max\left(0, \tau\left(L - \lambda\right)\right) \tag{6}$$

with the first derivative with respect to short-interest L (for $L > \lambda$) equal to $\frac{\partial c}{\partial L} = \tau$ for $L > 0$, which represents the marginal short-sale costs per unit with respect to short-interest.

Our implicit assumption is that the lending market is a perfectly functioning market, meaning that each stock borrower must pay the equilibrium cost per stock c and not the marginal cost of finding his own additional share. We can imagine a clearinghouse that collects the supply and demand schedule and then sets the equilibrium price for lending accordingly. The passive investors earn the rents from lending their shares but, by assumption, this does not affect their decision to hold the underlying shares. Similarly, those who can find shares to borrow at a cost of less than c are (effectively) assumed to lend those shares out at the equilibrium cost of c.

If $L^s = L^d$ we get the lending market clearing condition:

$$p = \left(\frac{1}{\tau}c + \lambda\right)\gamma\sigma^2 + (V - \alpha V) + c \tag{7}$$

4.5 Equilibrium

In equilibrium, both the stock and the lending market clear. The equilibrium short-sale costs c^*, equilibrium price p^* and equilibrium short-interest L^* come from Equations (3) and (7):

$$c^* = max\left\{\frac{2\tau(\alpha V - \lambda\gamma\sigma^2)}{\tau + 2\gamma\sigma^2}; 0\right\} \tag{8}$$

$$p^* = V + \frac{c^*}{2} \tag{9}$$

$$L^* = \frac{\alpha V - \frac{c^*}{2}}{\gamma\sigma^2} = min\left\{\frac{\alpha V}{\gamma\sigma^2}; \frac{2\alpha V + \lambda\tau}{\tau + 2\gamma\sigma^2}\right\} \tag{10}$$

Corollary 2: *Equilibrium short-sale costs c^* and consequently mispricing increase with divergence-of-opinion α, search costs τ and decrease with institutional lending supply λ, speculators' risk aversion γ, and volatility of the stock σ^2.*

Equation (8) reflects that, in this setting, if the pessimist's demand for a correctly priced stock $\left(\frac{\alpha V}{\gamma\sigma^2}\right)$ is smaller than the available institutional lending λ, then competition between the institutional lenders drives the cost of borrowing to zero, i.e., $c^* = 0$. In this case, both optimistic and pessimistic views are fully incorporated in the price, so the stock price reflects the average valuation which equals the fundamental value, $p^* = V$. However, Equation (8) also shows that if zero-cost pessimistic demand exceeds λ, then locating shares to borrow requires search costs and a positive c^* emerges in equilibrium. In this case, Equation (10) shows that the pessimist shorts fewer shares, resulting in a price higher than the fundamental value ($p^* > V$) as reflected in Equation (9). Equation (10) further shows that equilibrium short demand is equal to zero-cost shorting demand $\frac{\alpha V}{\gamma\sigma^2}$ if $c^* = 0$ and equal to $\frac{2\alpha V+\lambda\tau}{\tau+2\gamma\sigma^2}$ if $c^* > 0$, i.e., the parameters of the lending supply curve enter equilibrium if and only if a positive c^* emerges in equilibrium. As $\lambda\tau \leq \tau$, equilibrium shorting demand is then equal or smaller than the zero-cost shorting demand. The difference between zero-cost shorting demand and L^* if $c^* > 0$ is increasing in search costs τ and decreasing in institutional lending supply λ.

Corollary 3 *: If $\frac{\alpha V}{\gamma\sigma^2} > \lambda$, then $c^* > 0$, $L^* < \delta$, and $p^* > 1$. That is, there is mispricing and positive short-selling costs.*

When disagreement is zero ($\alpha = 0$), then $c^* = L^* = 0$. If $\alpha > 0$, demand for borrowing will be positive and the number of shares that will be borrowed depends on the amount of disagreement. For tiny α, the perceived benefits for the pessimist to shorting are small. Thus, the search costs that will be expended must be small, which will only be true if borrowing is approximately equal to the institutional lending supply. For a larger value of α, demand for borrowing rises, as the pessimist with a low private valuation is willing to borrow at higher costs. The equilibrium lending fee and short interest increase monotonically in α.

INSERT Figure 5 HERE

Figure 5 illustrates the model's equilibrium by simultaneously varying two of the five parameters (divergence-of-opinion α, search costs τ, institutional lending supply λ, risk aversion γ and risk σ) while holding fixed the other three. In Panel A, $\tau = 2$, $\gamma = 1$ and $\sigma = 1$. Mispricing increases linearly with divergence-of-opinion α. However, mispricing only occurs when $\frac{\alpha V}{\gamma\sigma^2} > \lambda$; hence the diagonal threshold to the left of which we see no mispricing. Decreasing λ linearly increases the mispricing. Accordingly, short-interest increases more quickly when costless lending supply is not exhausted yet and short-interest immediately reflects the full demand of pessimists, and, regardless of α, we observe no mispricing. To the right of this barrier, short-interest exhibits a flatter slope, when shorting additional shares induces search costs.

In Panel B, $\gamma = 1$, $\lambda = 0.1$ and $\sigma = 1$, i.e., 10% of the passive investors are willing to lend out their shares for free. Mispricing is severe for high search costs, i.e., for high values of τ. For a given level of divergence-of-opinion α, mispricing is a convex function of τ – more convex, the higher the divergence-of-opinion. Pertinently, short-interest decreases concavely with τ, eventually approaching the limit of α when search-costs approach zero.

Panel C illustrates how λ only has a large influence on the price if τ is large, because otherwise short-interest is large, in light of small search costs. Panel D finally shows the influence of risk aversion γ. On the right, we can see how there is no speculation and no mispricing as long as the speculators are risk-averse enough. Only for smaller risk aversion and smaller risk (σ), we observe a convex increase in mispricing and short-interest. In the limit, when speculators approach risk neutrality ($\gamma \to 0$) mispricing peaks.

4.6 Model with an Excessive Optimist and an Arbitrageur

The outlined model can easily be modified to capture the interaction between an excessive optimist and a rational arbitrageur with high risk bearing capacity.[14] The optimist demands $x_O = \frac{V(1+\alpha)-P}{\gamma_O \sigma^2}$ stocks, as before. The pessimist is substituted with an arbitrageur who knows the fundamental value V. The arbitrageur is willing to short sell for prices above $V \mp c$ and shorts $-x_A = \frac{P-(V+c)}{\gamma_A \sigma^2}$. We assume that the arbitrageur's risk-bearing capacity is much higher than the risk-bearing capacity of the optimist. Expressed in terms of risk aversion, this implies $\gamma_A \ll \gamma_O$. Solving the model yields $P = \frac{\gamma_A(V(1+\alpha))+\gamma_O(V+c)}{\gamma_O+\gamma_A}$ and $c = max\left(\frac{\tau\alpha V - \lambda\tau\sigma^2(\gamma_O+\gamma_A)}{\sigma^2(\gamma_O+\gamma_A)+\tau}; 0\right)$. It is straightforward to show that $\lim_{\gamma_A \to 0} P = V + c$. Stocks only become mispriced if shorting demand exceeds free lending supply and a positive c results in equilibrium. Mispricing caused by a positive shock to α follows the same comparative statics as in the base model. An alternative way of interpreting our empirical strategy is therefore the identification of mispricing caused by excessive optimism that cannot be completely arbitraged away due to high shorting fees.

5 Dynamics of Beliefs

5.1 Stylized Facts about the Dynamics of Beliefs

Before we move on to a dynamic version of the model, it is helpful to establish several basic stylized facts about the dynamics of beliefs. First, it is important to acknowledge the close relationship between excessive optimism and disagreement. A shock to disagreement in the classical sense implies an increase in the range of beliefs – an equal rise in pessimism as in optimism. Hence, such a shock affects the variance of the belief distribution but leaves the mean of the distribution unchanged. If we instead assume that only the right side of the distribution is affected, i.e., optimists become even more optimistic, while pessimists do not change their beliefs, we also experience an increase in variance, but this time it is accompanied by an increase in the mean of the distribution as well. As noted in the previous chapter, pessimists could even be much closer to the true fundamental value and be labeled arbitrageurs.

In this subsection, we use earnings forecast dispersion data as a proxy for any form of disagreement (and remain agnostic about which form it is), and examine using this proxy how disagreement evolves over time. While earnings forecast dispersion has been used in the literature to proxy for disagreement, it is only available for larger stocks where we typically do not observe binding short-sale constraints. For example, only 9% of the stock-month observations that we identify to have low institutional ownership (i.e., in the bottom quintile) have non-missing earnings forecast dispersion. Hence, to study returns, we will resort to the proxy

[14] See Blocher, Reed, and Van Wesep (2013), Appendix A, for a similar exercise.

generated by our model, i.e., a high past return accompanied by a high change in short interest. By doing so, we assume that dynamics of earnings forecast dispersion apply to the dynamics of latent disagreement of all stocks in general, including those where earning forecast dispersion is not available.

INSERT Table 1 HERE

To analyze the dynamics of beliefs, we first sort stocks into 10 portfolios based on the preceding year's change in earnings forecast dispersion. Table 1 presents some descriptive statistics. We can check our hypothesis that an increase in disagreement in the past is followed by resolution of disagreement. As described in the introduction, Figure 3 plots earnings forecast dispersion from 1 year before until 5 years after portfolio formation. The high change portfolio distinctly reverses to a similar level as before within roughly 5 years, thus confirming the resolution of disagreement hypothesis. The second highest change portfolio already exhibits a much lower increase in disagreement, indicating that large changes are very rare. There seems to be a small predictability in the other direction, as the low change portfolio slightly bounces up after portfolio formation. This increase is tiny in magnitude compared to the predictability of the high change portfolio, though, and the level arrives nowhere near its previous high, but rather in the neighborhood of all other stocks after 5 years.

INSERT Table 2 HERE

In Table 2 we predict future changes in earnings forecast dispersion over 1 year with positive and negative earnings forecast dispersion changes over the past year, using the Fama and MacBeth (1973) procedure. The results confirm that positive past changes strongly predict negative future changes. In contrast, including negative past changes to the regression barely increases the time-series average of the cross-sectional R^2. The coefficient estimate for positive past changes is larger by an order of magnitude than that of the negative past changes.

We conclude that the dynamics of beliefs approximately follow a two-state Markov process. Most stocks in the US cross-section have low levels of disagreement and fluctuate around that level. Occasionally, we observe large unpredictable jumps in disagreement. These are followed by resolution of disagreement, which is the only stylized fact we identify that is predictable with ex-ante available information. Except for this, past disagreement in beliefs does not help predict future disagreement. In particular, stocks where disagreement came down in the past are not more likely to become high disagreement stocks in the future again than other stocks.

5.2 Dynamic Model

Based on the dynamics of beliefs, price predictability in our model should arise after a disagreement shock for a constrained security. Intuitively, the set of optimistic agents will want to buy more shares, and in our setting they can only do so if the pessimists short-sell these shares. As in our static model, the institutional friction that drives our model is that, in order to short sell a share, a pessimistic agent must first borrow that share. When shares are hard to borrow because institutional holdings are low, the demand drives up the borrowing cost/lending fees. Due to the now high borrow costs, the opinions of the pessimistic agents are not fully reflected in their aggregate demand, and the share price rises. However, in a dynamic setting, news about the security's cash flows are released over time. As the optimists and pessimists observe these fundamental shocks, they will revise their views up or down in a way consistent with this new information. In this way, the disagreement is gradually resolved, leading to a gradual decline in the price.

We extend our static model to a multiperiod setup to capture this intuition. Agents trade an asset that will pay an uncertain liquidating dividend $\tilde{D}_T$ at time T. The fundamental value, $\tilde{D}_T$, is given by

$$\tilde{D}_T = D_0 + \tilde{\epsilon}_1 + \tilde{\epsilon}_2 + \cdots + \tilde{\epsilon}_T \tag{11}$$

where the fundamental shocks $\tilde{\epsilon}_t \sim \mathcal{N}(\mu_\epsilon, \sigma^2)$ are i.i.d. D_0 is a starting value that is common knowledge at the beginning of the first period. In each period t, traders observe the fundamental shock ϵ_t. As in the static model, traders have CARA preferences. Moreover, each period they trade based only on the current price, and their beliefs about the final payoff. That is, at time t they trade without anticipating that they will trade again before time T.

The mean of the fundamental shocks μ_ϵ is determined by nature at time 0. μ_ϵ is a realization of a normally distributed random variable with mean 0 and variance ζ^2, i.e., $\mu_\epsilon \sim \mathcal{N}\left(0, \zeta^2\right)$. μ_ϵ stays constant over all periods. Agents in our model do not directly observe μ_ϵ, but they do have a prior distribution. If they are unbiased, their prior distribution will accurately reflect the distribution from which μ_ϵ was drawn. However, as we will see in a moment, the optimists in our model have a prior distribution with a mean that is higher than 0, while the mean of the pessimists' prior distribution is less than zero. Over time, as they observe the sequence of shocks (ϵ_t's), both optimists and pessimists learn about the true mean by observing the sequence of fundamental shocks (see, e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998, for a similar modelling approach).

In each period, traders first observe the realization ϵ_t of the random variable $\tilde{\epsilon}_t$ and form their beliefs. Subsequently, trading takes place. After trading has taken place in the last period, there is no further news.

All agents agree that the value of the asset is equal to the sum of fundamental shocks D_T in period T, although they still do not know the true value of μ_ϵ with certainty.

To model the dynamics of disagreement, we assume that agents form beliefs at time t in a three-step procedure. In the first step, traders start with their prior belief. Specifically, just prior to observing the realization $\epsilon_t \sim \mathcal{N}(\mu_\epsilon, \sigma^2)$, they believe that $\mu_\epsilon \sim \mathcal{N}\left(\alpha_t^i, \eta_t\right)$, where i depicts the trader type, and where the belief of the optimists ($\alpha_t^O > 0$) and pessimists ($\alpha_t^P < 0$) differ. That is, the optimists believe that all future fundamental shocks will be drawn from a distribution with positive mean, and the pessimists believe that will drawn from a distribution with negative mean. In our specification, optimists and pessimists are equally uncertain about their view. We further assume that, before the first observation of a fundamental shock, the prior variance of all agents is equal to the variance of the distribution from which μ_ϵ has been drawn, i.e., $\eta_1^2 = \zeta^2$.

Traders then observe the realization ϵ_t of the random variable $\tilde{\epsilon}_t$. This realization serves as a signal about the unknown true mean μ_ϵ of $\tilde{\epsilon}_t$, and they (correctly) infer that the signal comes from a normal distribution with a mean equal to the unknown true mean μ_ϵ and variance σ^2.

Thus, in the second step, traders use Bayes' rule to combine their (biased) prior belief and the signal implicit in ϵ_t to form a posterior distribution for μ_ϵ. With two normal distributions, posterior beliefs are also normally distributed. The mean beliefs of the optimists and the pessimists are now $\hat{\alpha}_t^O = \frac{\alpha_t^O \sigma^2 + \epsilon_t \eta_t^2}{\eta_t^2 + \sigma^2}$ and $\hat{\alpha}_t^P = \frac{\alpha_t^P \sigma^2 + \epsilon_t \eta_t^2}{\eta_t^2 + \sigma^2}$, respectively. The posterior variance of both beliefs is $\hat{\eta}_t^2 = \frac{\eta_t^2 \sigma^2}{\eta_t^2 + \sigma^2}$.

We can write the mean belief of the optimist as

$$\mathbb{E}_t^O \left\{D_T\right\} = D_t + \hat{\alpha}_t^O (T - t). \tag{12}$$

and the mean belief of the pessimist as

$$\mathbb{E}_t^P \left\{D_T\right\} = D_t + \hat{\alpha}_t^P (T - t). \tag{13}$$

where $D_t = D_0 + \sum_{s=1}^{t} \epsilon_t$. Equations (12) and (13) reflect the fact that the time t expectation of the liquidating dividend $\tilde{D}_T$ is just the sum of D_t plus the expected value of all future fundamental shocks until time T. The variance of the predictive return distribution for the upcoming realizations of $\tilde{\epsilon}_t$'s is $\hat{\sigma}_t^2 = \sigma^2 + \hat{\eta}_t^2$ in both cases.[15] The variance of the sum of all remaining fundamentals shocks is $\hat{\sigma}_t^2 (T - t)$.

[15] See Brandt (2010) for a discussion of how to deal with parameter uncertainty in portfolio choice problems. The case of a single risky asset with unknown mean, known variance, normal priors and normal likelihoods is discussed on p. 312.

In the third and final step, agents use the beliefs specified above in their optimization problem to determine their demand

$$x_t^O = \frac{\left(D_t + \hat{\alpha}_t^O (T-t)\right) - p_t}{\gamma^O \hat{\sigma}_t^2 (T-t)} \tag{14}$$

and

$$-x_t^P = \frac{p_t - \left(D_t + \hat{\alpha}_t^P (T-t) + c_t\right)}{\gamma^P \hat{\sigma}_t^2 (T-t)} \tag{15}$$

for the periods $t < T$. Demands depend on the time t expectations of D_T (see Equations (12) and (13)). In period T, all fundamental shocks are realized and there is no room to disagree, so $x_T^O = x_T^P = 0$. Note that we now allow $\gamma^O \neq \gamma^P$.

Market clearing in the stock market implies

$$p_t^* = \frac{\left(D_t + \hat{\alpha}_t^O (T-t)\right)\gamma^P + \left(D_t + \hat{\alpha}_t^P (T-t) + c_t^*\right)\gamma^O}{\gamma^O + \gamma^P} \tag{16}$$

The market price p_t^* is a weighted average of the traders' beliefs. The market clearing shorting cost is

$$c_t^* = max\left\{0; \frac{\tau(T-t)(\hat{\alpha}_t^O - \hat{\alpha}_t^P - \lambda\hat{\sigma}_t^2(\gamma^O + \gamma^P))}{\tau + \hat{\sigma}_t^2(\gamma^O + \gamma^P)(T-t)}\right\} \tag{17}$$

As in the static model in 4.2, shorting costs increase in the aggregated degree of disagreement $(\hat{\alpha}_t^O - \hat{\alpha}_t^P)$ and the search costs τ and decrease in free lending supply λ. Shorting costs also increase in the length of time that remains until the resolution of uncertainty in $t = T$. Equation (16) shows that the equilibrium price p_t depends now on the observed realizations of $\tilde{\epsilon}$'s before the belief formation in t through the posterior beliefs $\hat{\alpha}_t^O$ and $\hat{\alpha}_t^P$. Large positive or negative realizations of $\tilde{\epsilon}_t$'s will cause the agents to revise their priors towards the direction of the observed signal.

What is left to be determined is how beliefs evolve over time. Our key assumption for the dynamics of disagreement is that agents take their last belief as the new starting value in the next period, i.e., $\alpha_{t+1} = \hat{\alpha}_t$, if no new disagreement shock arrives. This specification implies that, in the absence of a disagreement shock, optimists and pessimists will generally revise their priors towards the true fundamental value over time—disagreement is naturally resolved as new information arrives.

However, in the case of a new disagreement shock, agents adopt a new α_{t+1}. We can think of this event either as a reset of beliefs of current traders or as the drop-out of the old agents and the market entry of two new representative agents. Disagreement shocks are exogenous. Specifically, we assume

$$\alpha_{t+1}^{i} = \begin{cases} \hat{\alpha}_{t}^{i} & \text{if } \bar{\alpha}_{t+1}^{i} = 0 \\ \bar{\alpha}_{t+1}^{i} & \text{if } \bar{\alpha}_{t+1}^{i} \neq 0 \end{cases} \tag{18}$$

where $\bar{\alpha}_t$ are exogenous shocks to disagreement. Exogenous shocks to disagreement can be positive or negative (for example around earnings announcements).

The model nests several special cases. We briefly introduce the case of equal risk aversions ($\gamma = \gamma^O = \gamma^P$). Then equilibrium prices and shorting costs simplify to

$$p_t^* = D_t + \frac{(\hat{\alpha}_t^O + \hat{\alpha}_t^P)(T-t)}{2} + \frac{c_t^*}{2} \tag{19}$$

and

$$c_t^* = max\left\{0; \frac{\tau(T-t)(\hat{\alpha}_t^O - \hat{\alpha}_t^P - 2\lambda\hat{\sigma}^2\gamma)}{\tau + 2\hat{\sigma}^2\gamma(T-t)}\right\} \tag{20}$$

Figure 6 illustrates an example. The figures are based on Equations (19) and (20). There is a disagreement shock in period 3 and there are sizeable fundamental shocks of the same magnitude in periods 3 and 4. We set $\epsilon_3 = \epsilon_4 = 0.1$ and $\bar{\alpha}_3^O = -\bar{\alpha}_3^P = 0.2$. There are no further disagreement shocks. Fundamental shocks in periods 5 to 15 are all equal to the unbiased posterior belief in period 4, i.e., $\epsilon_t = 0.04\overline{6}\ \forall t \in [5, 15]$. An unbiased agent in this economy would start with a prior belief of 0 for the unknown mean μ_ϵ and then update this belief based on the observed fundamental shocks using Bayes' rule. The fundamental shocks in periods 5 to 15 are chosen in such a way that the unbiased expectation of μ_ϵ stays constant until the final period. We use $\zeta^2 = 0.25$ in this example. The time series of the resulting unbiased expectations is denoted with $\mathbb{E}_t\{D_T\}$. We also plot the time series of the model's equilibrium price for several different levels of free lending supply λ. For $\lambda = 0.8$, zero-cost lending demand is always below free lending supply and there are no price effects through costly lending. For λ equal to 0.4, 0.2, 0.1 and 0, free lending supply is exhausted in some periods and positive shorting costs emerge in equilibrium. Prices are higher than $\mathbb{E}_t\{D_T\}$, more so, the less free lending supply is available. Over time, disagreement fades out and with this fade-out prices converge back to $\mathbb{E}_t\{D_T\}$. Prices equal expectations if free lending supply is sufficiently large to absorb all demand.[16]

INSERT Figure 6 HERE

[16] Figure C.1 in Appendix C shows a figure with equilibrium prices for a negative fundamental shock.

5.3 Empirical Implications

What leads to overpricing in the model is a positive shock to *divergence-of-opinion*, where demand from the arbitrageur or pessimist to borrow shares exceeds the supply from the passive investors. Empirically, we can directly observe changes in short-interest, which is the key part of both the proxy for a *shock to divergence-of-opinion* and *becoming expensive to short.* The former is computed by combining the change in short-interest with the firm's past return. In order to become expensive to short, the firm additionally needs to have low institutional lending supply, which we proxy with observable institutional ownership. We assume that an unknown fraction of institutions is willing to provide (virtually) costless lending. So in reality, institutional ownership should be roughly proportional to institutional lending supply, where we assume the coefficient of proportionality to be equal for all stocks. Furthermore, we assume that search costs for finding additional shares to borrow after institutional lending is exhausted are similar and non-zero for the whole universe of stocks. Thus, we simply need to find those stocks with *low institutional ownership* that experience a *large return* and a *large change in short-interest* at the same time. These should be the stocks with the biggest identifiable overpricing and the model therefore predicts low returns going forward, as a consequence of the resolution of disagreement.[17]

Empirically, we will often see large returns due to changes in fundamental value. The key to distinguish these from shocks to divergence-of-opinion is to focus on those that go hand-in-hand with changes in short-interest. Shocks to disagreement and shocks to fundamental value are both likely to be contemporaneous with news arrival. Hence, if a low-lending-supply stock experiences positive news, which is not interpreted in the same way by everybody, one part of the large observed return will be the change in fundamentals and another part will be due to the change in beliefs. Accordingly, the reversal need not be as large as the return in the first place.

Note that there are other reasons for short selling, such as hedging, arbitrage or even tax-considerations (Brent, Morse, and Stice, 1990). Additionally, technical trading rules could trigger large amounts of short-sales. Momentum, e.g., dictates short-sales when a stock has experienced large negative returns. Again, focusing on the occurrence of large changes in short-interest accompanied by large *positive* returns helps to empirically distinguish technical shorting demand from shorting demand caused by divergence-of-opinion by assuming that the technical shorting demand for stocks with large positive past returns is virtually zero.

[17] It should be noted that stocks for which short-selling is nearly impossible (i.e., where $\tau \to \infty$ and $\lambda \to 0$) will be the most mispriced – but they cannot be identified empirically since short-interest and changes in short interest will be close to zero (see Figure 5 Panel C).

6 Empirical Results

6.1 Overpricing Among Winners

The model predicts that stocks with a shock to divergence-of-opinion can be identified with a large past return and a large change in short-interest (Prediction 1). If such a stock additionally has low institutional lending supply, which we empirically proxy with institutional ownership, short-sale costs will be high. As a consequence, the stock will be overpriced and will experience a low future return (Prediction 2).

The model provides no guidance for the distance between periods $t = 0$ and $t = 1$, i.e., the time-period over which the past return and the change in short-interest should be calculated. As a first cut, we use a one-year (12 month) period, skipping the return in the last month before portfolio formation. Given the 12-month return measurement period we have selected, high past returns will proxy both for changes in disagreement, and for changes in fundamental value. Further, assuming that the momentum effect is a result of continuing incorporation of fundamental information, the high past returns of our sample of firms may result from either positive shocks to fundamental value *or* from shocks to disagreement. Our short-sale constrained, high past return firms *could* therefore have higher average returns than the average firm in the sample because of the momentum effect. The key prediction of our model is *not* that these firms earn low future returns relative to the average firm in the economy, but rather that they earn lower returns than unconstrained, high-past return firms.

We measure changes in short-interest over the same 11-month period. Since short-interest is always reported in the middle of the month, we shift its ranking window two weeks to the right, i.e., while returns are measured from the beginning of month $t - 12$ to the end of month $t - 1$, the change in short-interest ΔSIR is calculated as the difference of the level from two weeks ago vs. eleven-and-a-half months ago.

We single out candidate overpriced stocks by triple sorting: We first divide the universe of stocks into quintiles according to their past return. Within each group, we independently sort on the change in short-interest ΔSIR and the level of institutional ownership IOR – again into quintiles. Making this an independent sort helps get more independent variation in both variables.[18] The five-by-five-by-five sort provides us with 125 portfolios. Each portfolio is value-weighted, both to avoid liquidity-related-biases associated with equal-weighted portfolios, and to ensure that the effect we document is not only driven by extremely low market capitalization stocks.

[18] As a robustness check, we present results from a 5x5x5 sequential conditional sort in Appendix E, where we first sort into quintiles based on past return, then, conditional on that, into quintiles based on institutional ownership and then, again conditional on the latter, into quintiles based on change in short-interest. Results are, as expected, less extreme, but still highly statistically significant.

Our model's main empirical prediction is that identified overpriced stocks will have low returns going forward, as disagreement is resolved. Table 3 reports the one-month-forward return of the 25 winner portfolios (Panel A) and 25 loser portfolios (Panel B).[19] The stocks where we expect the largest overpricing, i.e., past winners with the lowest institutional ownership and with the largest change in short-interest (bottom right corner portfolio), have an excess return of -1.66% per month, on average. This number appears particularly large in magnitude when compared to the other winner portfolios. While its direct row/column neighbors also seem slightly affected, all other winner portfolios feature large excess returns with an average around 1% per month. Comparing it to the high institutional ownership stocks, while remaining in the winner and high ΔSIR row, results in a difference of -2.71% per month with a Newey-West t-statistic of -5.03. This difference cannot be explained by the three Fama and French (1993) factors (FF3), as can be seen in the rightmost column. Similarly, taking the column's bottom vs. top difference produces an excess return of -2.24% per month (t-statistic (-3.89)) which can also not be explained by FF3.

In our empirical analysis, we concentrate on the implications of our model for past winners. Nonetheless, it is interesting to see the effects of institutional ownership and changes in short-interest among losers. Panel B reveals that the bottom-right losers are also the ones with the lowest returns—in fact, even lower in absolute terms than the bottom-right winners. While the raw excess-return is quite large in magnitude, it is noteworthy that parts of these returns can be explained by a negative loading on the momentum factor, i.e., these stocks being extreme losers (Table 5 Panel C, Column 4). This is also confirmed, when looking at their past returns, which amount to -47% (Table 4 Panel C). Furthermore, going back to the regression results from Table 5 Panel C, the portfolio loads heavily on IVOL and the CME portfolio from Drechsler and Drechsler (2016), based on a sort on the ratio of short-interest to institutional ownership, and the alpha becomes insignificant when either of these factors is included. Table 4 Panel H shows that their pre-formation month's IVOL is indeed among the largest of all portfolios with 5.82%, while Panel B exposes them as micro stocks with a value-weighted average market capitalization of $0.33B.

INSERT Table 3 HERE

Coming back to past winners, Figure 7 proceeds to track the bottom right corner portfolio's abnormal (with respect to the three Fama and French factors) performance over the subsequent ten years after portfolio formation, by plotting its cumulative log-excess-return. We observe a steep significant decline within the first 18 months that slowly flattens out and becomes insignificant after roughly four to five years. In total, this hedged portfolio of the overpriced winners loses almost 70% in value over the first 5 years, on average. The poor performance observed in the first month seems to be highly persistent.

[19] The returns of the remaining 75 portfolios can be found in Appendix D.

INSERT Figure 7 HERE

Next, we check whether some of our model's secondary implications are reflected in the data. Our aim was to find stocks with high divergence-of-opinion. One empirical proxy for this is analyst forecast dispersion of fiscal-year-end earnings, calculated as the standard deviations normalized by the mean. They are displayed for the 25 winner portfolios in Panel M of Table 4. The bottom-right-corner winners apparently are the ones with the highest forecast dispersion with 35.31% among the winners. The average of middle, i.e. neither winner nor loser, portfolios is 10.54%. Only a number of loser portfolios exhibit larger divergence-of-opinion, while it is 32.48% on average among losers. However, our model makes no predictions about losers. Overall we can conclude that we do seem to pick up considerable divergence-of-opinion with our proxies. A natural question to ask would be why we do not use forecast dispersion directly as a proxy. First, this measure is not available for a considerable fraction of stocks, since we need forecasts of at least two analysts to be able to calculate a meaningful standard deviation. Additionally, we would induce a bias to our sample, as we would exclude precisely those firms, where such overpricing is more likely to happen, i.e., smaller firms with low regular analyst attention. Here, we use the measure as a sanity check, with the subset of stocks that our procedure selected, for which it actually is available.

INSERT Table 4 HERE

In addition, we also consider the change in forecast dispersion over the preceding 12 months in Panel N. As one can see, loser stocks tend to experience large shocks to this proxy for disagreement. In contrast, winners generally experience a decrease in disagreement over the formation period – except for the bottom-right corner winners. Here, forecast dispersion goes up considerably, by 15.50 percentage points.

INSERT Figure 8 HERE

Our main theoretical prediction further relies on the assumption that divergence-of-opinion (which can be based on excessive optimism) is resolved from period 1 to 2. In Figure 8 we plot the value-weighted average earnings forecast dispersion of the bottom right corner winners over five years subsequent to the formation period.[20] Disagreement quickly drops right after portfolio formation. The decrease continues for at least a year. The empirical pattern in this disagreement proxy is consistent with the empirical pattern in returns, as shown in Figure 7. Disagreement is resolved within roughly 12 to 18 months after portfolio formation, on average. The bulk of the corner portfolio's negative abnormal performance is realized in this time period.

[20] For the figure, we resort to a 3x3x3 sort, as earnings forecast dispersion is only available for a small subset of firms in our portfolios. For the corner winners in the 5x5x5 sort, this subset comprises 0 firms in 28% of months and less than 5 firms in 76% of months. The corner winners in the 3x3x3 sort have at least 5 firms with earnings forecast dispersion in 94% of the time.

The model also predicts that the selected stocks became very expensive to sell short. To examine this, we calculate two additional measures. Panel I of Table 4 displays SIRIO, i.e., the number of stocks currently being shorted (short interest) divided by the number of stocks held by institutions (institutional ownership), following Drechsler and Drechsler (2016). This measure is particularly attractive as it has an interpretation within our model. It tells us how close or how far above we are to the institutional lending supply threshold. Assuming the unknown fraction of institutions that are willing to lend out for free is one, for instance, a SIRIO measure above 100% would indicate that the demand for short-selling is larger than institutional lending supply and thus, investors are willing to pay high search costs in order to still be able to short the stock. In Panel B of Figure 4 this would correspond to a situation where we are far above the kink in the lending supply curve and costs are now non-zero.

The numbers in Panel I of Table 4 clearly speak in favor of this phenomenon. On average, the bottom-right-corner winners exhibit a SIRIO of 238.34%, which suggests that they are substantially past the point of free lending and short-selling these stocks is really expensive. A second proxy for short-sale costs is calculated with options data. Following Cremers and Weinbaum (2010), we calculate the volatility spread at month-end of matched put/call option pairs. A large negative number indicates a strong deviation from put-call parity in the direction of the put-option being relatively expensive. This has been linked to short-sale constraints by, e.g., Ofek, Richardson, and Whitelaw (2004). Again, the bottom-right-corner portfolio stands out in Table 4 Panel J with a value of -5.29%.

Some basic characteristics about these portfolios are reported in Table 4. Panel A reveals that, on average, our portfolio of overpriced winners contains 16 stocks.[21] There are portfolios that contain substantially more, but it is not the smallest portfolio of all. The independent sort leads to an inverse u-shape with respect to portfolio size among low IOR stocks and a u-shape for high IOR stocks. Similarly, Panel B reveals that our portfolio's stocks have a value-weighted average market capitalization of \$2.33B.[22] Again, this is small, but far from the micro-cap threshold – in fact, this is well above the 40% quantile from December 2014 using NYSE breakpoints. Among the losers, numbers go down as low as \$160M for the portfolio containing the smallest stocks, on average.

Winners have gained a little over 100% over the 11-month ranking period (Panel C). The bottom-right-corner winners stand out with more than 200% returns. This seems consistent with the idea that their prices have substantially overshot. At the same time, short-interest has increased by 6.44 percentage points, which

[21] Appendix E contains, as a robustness check, results with a 3x3 instead of a 5x5 sort within the winner-quintile. This leads to more stocks in the portfolio of interest, but the underperformance of it remains strong and statistically significant.

[22] Excluding the 20% smallest stocks by market capitalization still results in large negative returns for the bottom-right corner portfolio, as reported in Appendix E. This should not come as a surprise, as our portfolios are value-weighted and hence dominated by their largest members. Also, our portfolio of interest does not contain the smallest stocks, as these are located to a large part within the loser quintile.

is the largest number in the whole high change in short-interest row. That is quite surprising, as such a change would have been easier to achieve among stocks with a larger share of institutional ownership and accordingly larger institutional lending. Hence, this hints at our identification being successful in identifying stocks with large overpricing, where rational or pessimistic investors are willing to take on large search costs in order to short them.

Panel E confirms that our sort is successful in filtering out stocks with little institutional ownership. On average, 8.91% is being held by institutions for these stocks. The level of short-interest (Panel F) is large for the bottom-right-corner stocks, but the high IOR stocks' level is even higher. Also, stocks with a low change in short-interest tend to have a level of short-interest that is well above that of all three middle change portfolios. This suggests that there is a lot of persistent short-selling going on. This could, for instance, be for hedging purposes etc. Put differently, it is likely that the share of shorting activity that is due to speculation is much higher for stocks in the bottom-right corner portfolio than for high IOR stocks.

Another noisy proxy for mispricing can be a firm's book-to-market ratio. Panel G confirms that our identified stocks are the most expensive relative to their book-value among the winners, with a ratio of 18%, which is in line with their relative outperformance over the ranking period. In addition to this, these stocks exhibit the largest idiosyncratic volatility relative to a Fama and French 3-factor model within the month prior to portfolio formation (Panel H).

6.2 Trading Strategy

Based on the findings above, we construct a long-short portfolio that captures the discovered abnormal returns while hedging out systematic exposure to the market and standard momentum. We form a long-short portfolio by taking an equal (1/24) long position in each winner portfolio, except that containing the overpriced winners, and go short the portfolio of overpriced winners. This "Betting Against Winners" (BAW) strategy delivers an annual Sharpe-ratio of 1.08 and an annualized excess return of 31%, which corresponds to the monthly average excess return of 2.57% (t-statistic of 5.45) as displayed in Table 5, Column (1).

INSERT Table 5 HERE

We further explore the nature of the BAW portfolio by regressing its monthly returns on well-known factors. A CAPM-regression on the market excess-return reveals a slightly negative loading on the market and the alpha correspondingly increases moderately to 2.79% (column 2) compared to the raw excess return. Column (3) reveals a significantly negative loading on the SMB factor, indicating that our overpriced winners tend to co-vary with small stocks. However, the alpha is almost the same as before and the t-statistic remains large. When we include the standard Carhart (1997) momentum factor, the alpha remains virtually unaffected. The loading on the momentum factor (MOM) is 0.03. Hence, our BAW portfolio is momentum-neutral – a consequence of being long and short past winner stocks. Column (5) shows that BAW also does not significantly load on IVOL (Ang, Hodrick, Xing, and Zhang, 2006). Interestingly, its inclusion drives out the significant SMB loading. The abnormal return is at 2.56% with a t-statistic of 5.94. The portfolio furthermore neither loads on the Pastor and Stambaugh (2003) liquidity factor[23] nor on a short-term reversal factor.[24] Not surprisingly, the BAW portfolio loads positively on the CME portfolio, as the BAW portfolio is short in stocks that should be expensive to short according to our model. The alpha's decrease after inclusion of the CME factor, but the CME portfolio is only able to explain part of the returns to the BAW trading strategy. Even if we include all factors simultaneously (column 9), BAW still has an abnormal return of 1.86% with a t-statistic of 4.20. We can conclude that the BAW portfolio cannot be explained by exposure to any commonly used factor and is distinct from other asset pricing puzzles. Panel B repeats the analysis with excess returns of just the short-side of BAW, i.e., returns of low IOR, high change in SIR winners less the risk-free rate. It becomes apparent, that most of the conclusions above stem from the short-side of BAW, i.e., from the "overpriced" winners.

Figure 9 plots the cumulated log-returns of the BAW portfolio and six well-known long-short strategies over the full sample period from June 1989 to December 2014. The BAW portfolio dwarfs most other strategies, such as the FF3-factors. Momentum and IVOL perform similarly well until the early 2000s, but go virtually flat afterwards. Consistent with its high Sharpe-ratio, the BAW portfolio almost always performs well, rarely experiences long down-phases and quickly recovers from short-term drops. Notably, it does not experience severe "crashes", such as momentum in the aftermath of the dotcom bubble or the financial crisis, when markets rebounded (Daniel and Moskowitz, 2016). It also continues its striking performance throughout the last decade, a feature that only the market excess return and betting-against-beta (BAB) are capable of offering.

INSERT Figure 9 HERE

Whether or not these large abnormal returns can be earned by investors remains an empirical question, on the other hand. The stocks in the bottom-right-corner portfolio are precisely the ones that we hypothesize to be expensive to short. Almost certainly, shorting these stocks will be expensive. In order to assess the profitability of the BAW portfolio as a trading strategy, we would require data on actual loan-fees.

[23] The liquidity factor time series is downloaded from Lubos Pastor's website at http://faculty.chicagobooth.edu/lubos.pastor/research/ (last accessed on February 25, 2016).

[24] Short-term reversal is calculated as the return of the average of small and large recent losers minus the average of small and large recent winners from a 2x3 independent sort on market capitalization and past month's return using NYSE breakpoints, closely following the instructions on Ken French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_st_rev_factor.html (last accessed on February 25, 2016).

6.3 Returns of Constrained Winners after Earnings Announcements

One point in time when disagreement is likely to be resolved is when firms announce their earnings (see, e.g., Berkman, Dimitrov, Jain, Koch, and Tice, 2009), which usually happens once per quarter. Figure 10 displays average log excess returns of constrained winners as well as all other winners around the first earnings announcement after portfolio formation, i.e., within the first three months. Consistent with Aboody, Lehavy, and Trueman (2010), winners generally underperform after earnings announcements and slightly outperform in the days leading up to the announcement. Constrained winners, however, lose considerably and significantly more on the first three days following the announcement.

INSERT Figure 10 HERE

Summing up the three point estimates (those that are significantly smaller than zero) gives a cumulated log excess return of -2.32%. The cumulated log excess return earned in the first quarter after portfolio formation is -3.46% in total. Thus, 67% of the negative returns of constrained winners within the first three months are accumulated around earnings announcements.

6.4 Equity Issuance of Constrained Winners

Financial economists have now accumulated substantial empirical evidence consistent with the view that manager's try to time the market in their capital structure choices (see Baker and Wurgler, 2002, and the references therein). CFO's themselves state that they are reluctant to issue equity if they perceive their market valuation to be below the fundamental value (Graham and Harvey, 2001). Following this logic, managers who view their equity to be overvalued should issue equity to let current shareholders benefit from high market valuations. Although, perceived overvaluation is much less common than perceived undervaluation among corporate managers (Graham and Harvey, 2001, p. 219), we hypothesize that at least some managers of firms in the constrained winner portfolio think their equity is overvalued.

To test this idea, we look at the composite equity issuance measure of Daniel and Titman (2006). They define this quantity as the part of the change in a firm's market capitalization that cannot be explained by a firm's stock return (see also Pontiff and Woodgate, 2008). We build the composite equity issuance measure for each firm over a six-month time period, starting three months before portfolio formation (at the beginning of month t) and ranging to three months after portfolio formation. The individual measure is defined as

$$\iota_{t-3,t+2} = \log\left(\frac{ME_{t+2}}{ME_{t-3}}\right) - \log\left(1 + r_{t-3,t+2}\right) \tag{21}$$

where t is the first month after portfolio formation. The composite equity issuance measure of a portfolio is calculated as the value-weighted average of individual composite equity issuance measures. We build $\iota_{t-3,t+2}$ for all 25 winner portfolios. The quantity measures the net effect of all issuance activity like equity issues, employee stock option plans, share repurchases or cash dividends around the time of portfolio formation, i.e., around the time where constrained winners are supposed to be overpriced due to a positive shock to disagreement.

INSERT Table 6 HERE

Table 6 presents the results. Consistent with previous literature, winner stocks tend to issue equity on average. Furthermore, net issuance activity seems to decrease with institutional ownership. The number that stands out in Table 6 is the 12.85 in the bottom-right corner, showing that 12.85 percentage points of the increase in market capitalization of constrained winners cannot be attributed to their stock returns. Constrained winners as a group are therefore much higher net issuers of equity than the groups of firms in any other winner portfolio, consistent with the idea that managers of these constrained winners consider their equity to be overvalued and that they are trying to use this window of opportunity in favor of their shareholders. Given that most managers appear to be overoptimistic regarding their own firm's prospects (Ben-David, Graham, and Harvey, 2013), we consider the differences in the composite equity issuance measure to be substantial.

INSERT Figure 11 HERE

Figure 11 tracks monthly composite equity issuance of the constrained winner portfolio over time in the months before and after portfolio formation (t=0). It becomes apparent that issuance activity peaks around portfolio formation, i.e., when we identify a stock to be most overpriced.

6.5 Speculator Attention and Short-Sale Constraints

Appendix B presents an extension of our model. Instead of modeling that there are just two representative investors – one optimist and one pessimist – we assume there a continuum of speculators with uniformly distributed beliefs on the interval $[V(1-\alpha); V(1+\alpha)]$. We further introduce a parameter δ which governs the total speculators' mass. Intuitively, δ can be thought of as capturing the quantity of speculators in the economy: a high δ can reflect the presence of a large number of speculators who are willing to put their capital at risk in betting on a particular stock. A cross-sectional interpretation of δ is attention; those stocks that get more attention of speculators have a higher δ.

Attention and risk aversion play a very similar role within the extended model, as they both govern the amount of speculative activity. Speculators borrowing and stock demand increases in attention and decreases in risk aversion. In fact, as shown in the Appendix, the limits of the equilibrium quantities are the same for $\delta \to \infty$ and for $\gamma \to 0$ in the extended model. The resulting empirical prediction is that increases in attention cause overpricing among short-sale constrained stocks. These stocks earn negative abnormal returns going forward.

There is already initial empirical evidence supporting this prediction. Da, Engelberg, and Gao (2011) show that an increase in the Google Search Volume Index for a stock ticker in one week leads to high returns over the two following weeks. Stock prices reverse within a year. Hillert and Ungeheuer (2016) use 90 years of media coverage of US firms in the New York Times. They find that firms with above median increases in media coverage outperform firms with above median decreases in media coverage by about 10% in the formation year. Subsequently, half of this return difference reverses over a three-year-period. Our model delivers the additional and – to the best of our knowledge – untested prediction that attention-driven stock price increases are concentrated among stocks with low institutional ownership. These stocks cannot be easily shorted by arbitrageurs or pessimists whose attention was directed to the firm. Our model further predicts that increases in attention are accompanied with increases in short interest.

7 Conclusion

Our model provides a simple framework for considering the effect of short-sale constraints and excessive optimism or disagreement about a stock's value when stock lending fees are endogenous. It generates clear-cut and testable hypotheses, and suggests that a high past return together with low institutional ownership and a large change in short-interest is a sign of a shock to optimism. This prediction strongly contrasts with the empirical regularity of price momentum; that high past return firms continue to experience high future returns. We argue that the reason the momentum effect remains strong among winners in aggregate is because relatively few firms are short-sale-constrained (consistent with the empirical evidence on the lending market presented by D'Avolio, 2002).

In most theoretical models designed to explain the momentum effect, the high past returns of "winner" stocks are a result of positive changes in fundamentals. Our model is different, in that it captures the effect of changes in optimism. Our model shows that, for constrained firms, positive shocks to optimism results in high contemporaneous returns, overpricing, and low future returns. For a sample of constrained firms that have experienced high returns over the past year, it is likely that both a positive fundamental shock and a shock to disagreement will have contributed to these high past returns. Going forward the two shocks—fundamental and optimism—have opposite effects on expected future returns. In general, resolution of divergence-of-opinion should dampen the momentum effect. For large optimism shocks among stocks that are difficult to short, the resolution effect may even dominate, consistent with our empirical findings.

Based on this idea, we isolate the high past-return firms with low institutional ownership and which experience large changes in short-interest over the preceding 12 months. We find that a value-weighted portfolio of this set of past winners earns future excess returns of -1.66%/month. After controlling for exposure to the Fama and French (1993) three factors, the Carhart (1997) momentum factor and the Ang, Hodrick, Xing, and Zhang (2006) idiosyncratic volatility factor, the magnitude of the unexplained return increases to -2.59%/month (t=-5.84). Also, in contrast to the shorter-horizon momentum returns, the negative excess returns of this portfolio continue for the next 4 years. Were it possible to short this portfolio of overpriced winners, and hedge this short position by buying a portfolio of non-short constrained winners, we show that such a strategy would generate a Sharpe-ratio of 1.08, and a strongly positive, highly significant alpha after controlling for standard factors.

Our analysis also speaks to the ongoing discussion about the presence of bubbles in financial markets. Fama states "Bubbles are special cases of market inefficiency where cumulative returns differ predictably from equilibrium expected returns for sustained periods."[25] We show that irrational run-ups in prices of constrained stocks lead to forecastable negative long-term returns, a pattern that could be labeled an individual bubble. Our empirical evidence shows that individual bubbles are identifiable in all time periods of our sample and are not only present in one specific time period.

Our results are supportive of the idea that short-sale constraints sideline more pessimistic market opinions, and, when they coincide with excessive optimism, result in overpricing. Based on a parsimonious model, we propose a simple empirical strategy for identifying a subset of stocks that became overpriced through this mechanism. The puzzle that remains is what the shocks are that are leading to excessive optimism, and to the resulting overpricing.

[25] From a 2002 email exchange between Eugene Fama and Ivo Welch; see http://www.ivo-welch.info/teaching/famaconversation.html, last accessed December 23, 2016.

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Figures

Figure 1: Cumulated log excess returns in 60 months after formation.
This figure plots the cumulated log excess return of four portfolios in the 60 months after portfolio formation (t=0). The portfolios are the market and the past-winner (past-loser) portfolio, a value-weighted combination of the 20% of the stocks with the best (worst) cumulative return over the period from month t-12 through month t-2. The constrained-winner portfolio is a value-weighted portfolio of winners with low institutional ownership (smallest 20% at formation) and a high change in short interest over the preceding year (20%-quintile).

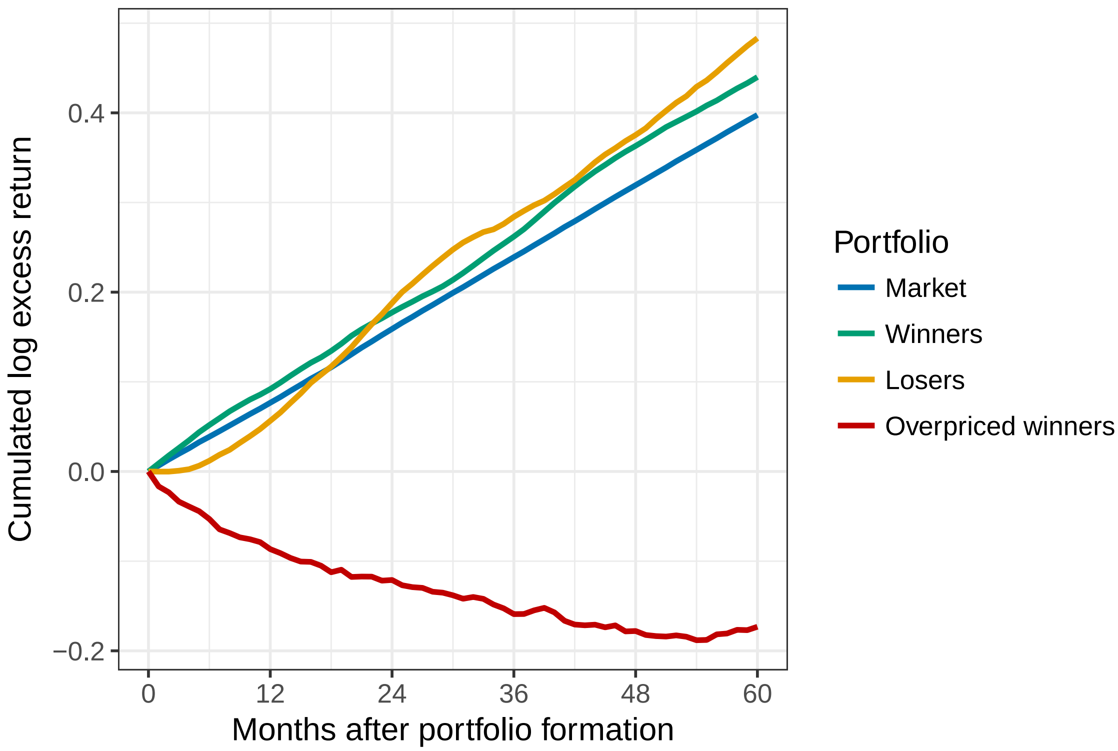


Figure 2: Performance of hedged past-winners, past-losers and constrained winners.
This figure presents the time series of values for a set of hedged portfolios: the past-winner (past-loser) portfolio in month t is a value-weighted combination of the 20% of the stocks with the best (worst) cumulative return over the period from month t-12 through month t-2. The constrained-winner portfolio is a value-weighted portfolio of winners with low institutional ownership (smallest 20% at formation) and a high change in short interest over the preceding year (20%-quintile). To calculate the portfolio value, we assume an investment at the beginning of June 1989 of $1,000, which is invested in the portfolio. We also assume that the exposure to Mkt-RF, SMB and HML are hedged. We calculate the hedging coefficients by running a full-sample regression of the portfolio returns on Mkt-RF, SMB, and HML. Then, using the full-sample regression coefficients, we subtract the returns of the (zero-investment) hedge-portfolio $[b_{\mathrm{Mkt}}(R_{\mathrm{Mkt}}\text{-}R_{\mathrm{f,t}})+b_{\mathrm{SMB}}\mathrm{SMB}_{\mathrm{t}}+b_{\mathrm{HML}}\mathrm{HML}_{\mathrm{t}}]$ from the past-winner returns to generate the hedged portfolio returns.

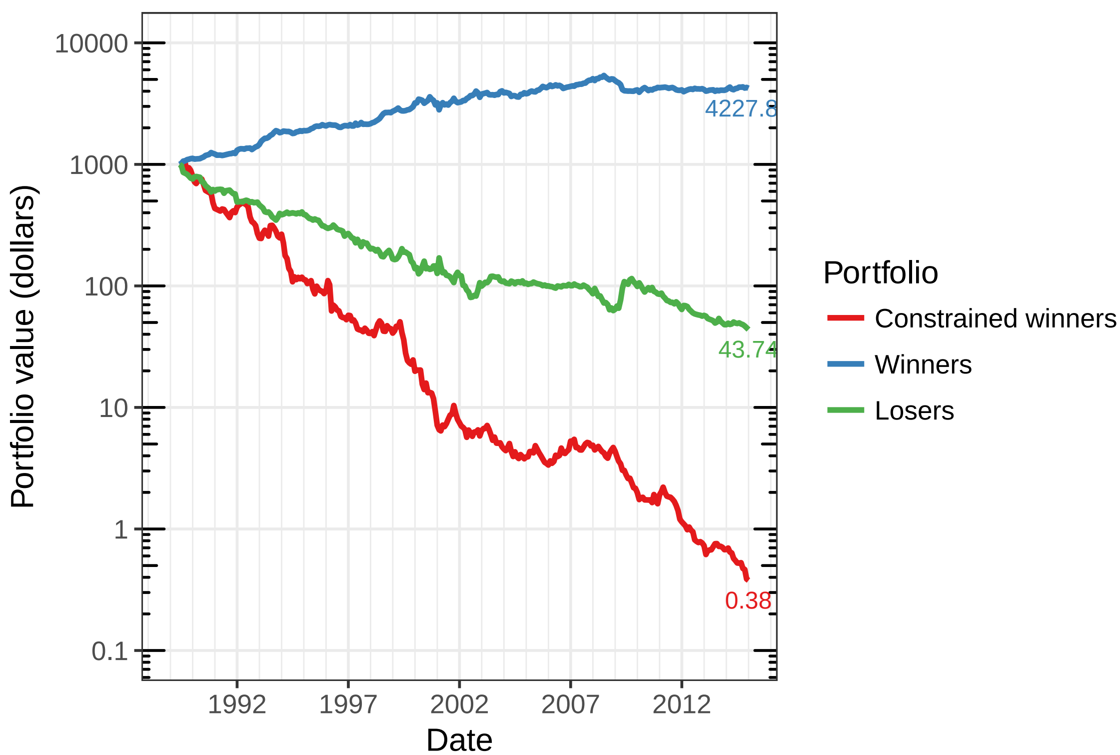


Figure 3: Dynamics of earnings forecast dispersion.
Stocks are sorted based on their past 1-year change in earnings forecast dispersion into 10 portfolios. Their level of earnings forecast dispersion is tracked over time, from 12 months before until 60 months after portfolio formation (t=0).

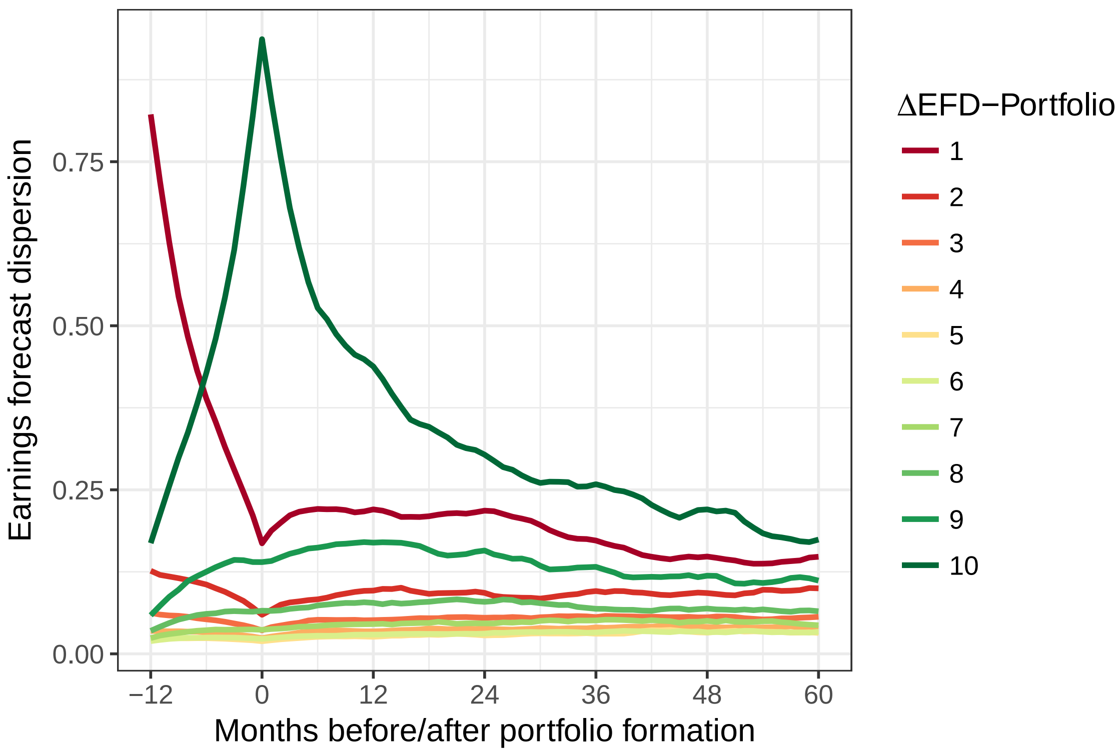


Figure 4: Supply and demand in the stock and the lending market.
This figure shows the supply and demand functions in both the stock (Panel A) and the lending market (Panel B). Market clearing occurs at their respective intersections. S^d is stock demand and S^s is stock supply, p is the stock price, δ scales the demand of speculators relative to stock supply and α is a measure for divergence-of-opinion. L^d is lending demand and L^s is lending supply, c is the cost of borrowing and λ represents institutional lending supply. In Panel A (Panel B), we draw supply and demand curves assuming that c (p) stays constant if p (c) is varied.

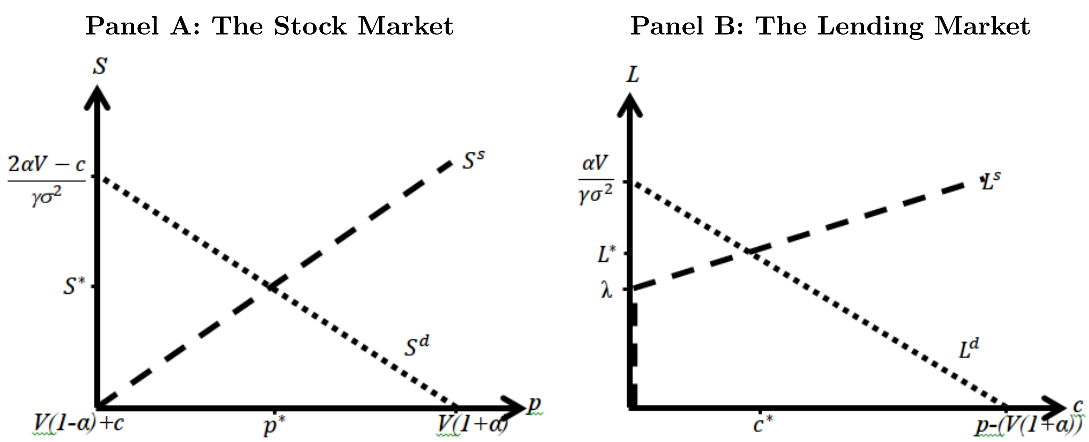
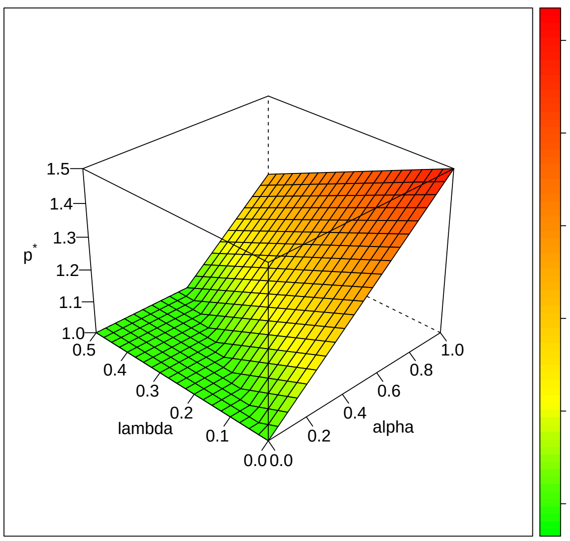


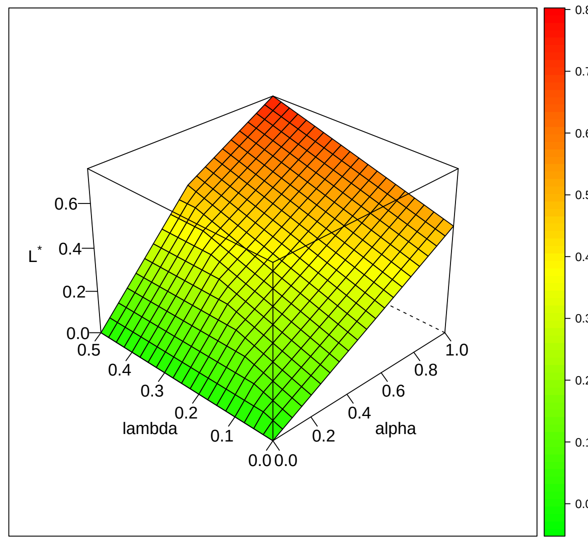
Figure 5: Equilibrium price and short-interest with varying parameters.
This figure shows the equilibrium price p^* and the equilibrium short-interest L^* with variations of two of the model's six parameters holding fixed the other four. Fundamental value V is always equal to 1. Panel A varies α and λ, while fixing $\tau = 2$, $\gamma = 1$ and $\sigma = 1$. Panel B varies α and τ, while fixing $\lambda = 0.1$, $\gamma = 1$ and $\sigma = 1$. Panel C varies λ and τ, while fixing $\alpha = 0.5$, $\gamma = 1$ and $\sigma = 1$. Panel D varies γ and σ, while fixing $\alpha = 1$, $\tau = 0.5$ and $\lambda = 0.1$.

Panel A: $\tau = 0.5$; $\gamma = 1$; $\sigma = 1$

Equilibrium price p^*

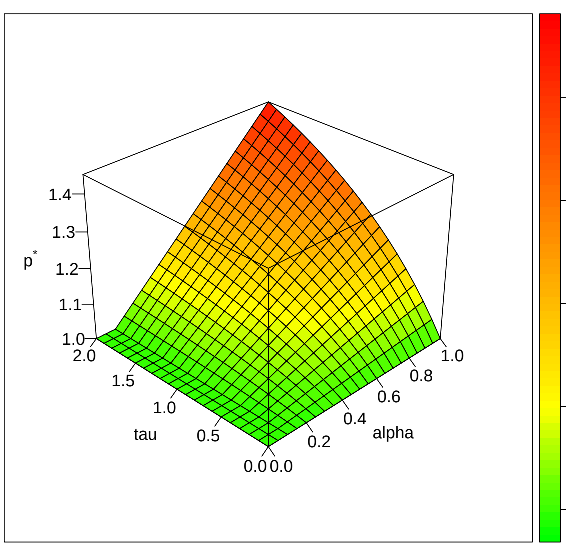


Equilibrium short-interest L^*

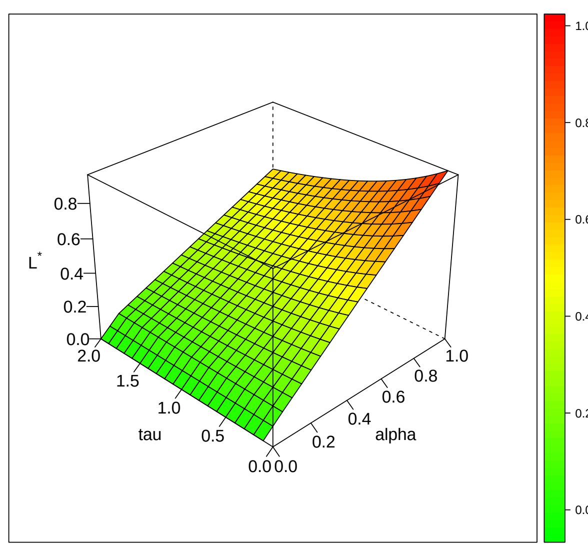


Panel B: $\lambda = 0.1$; $\gamma = 1$; $\sigma = 1$

Equilibrium price p^*

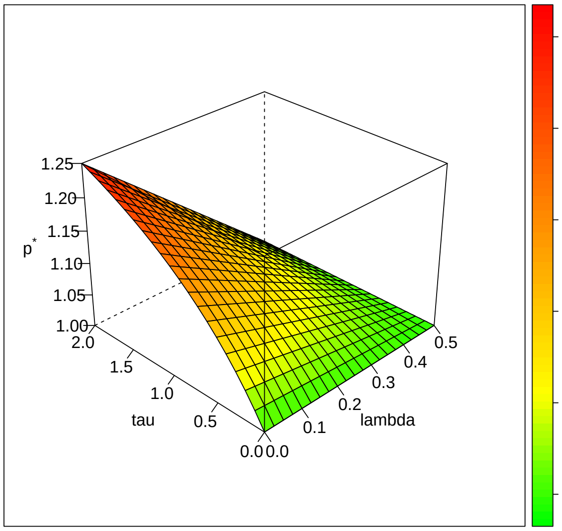


Equilibrium short-interest L^*

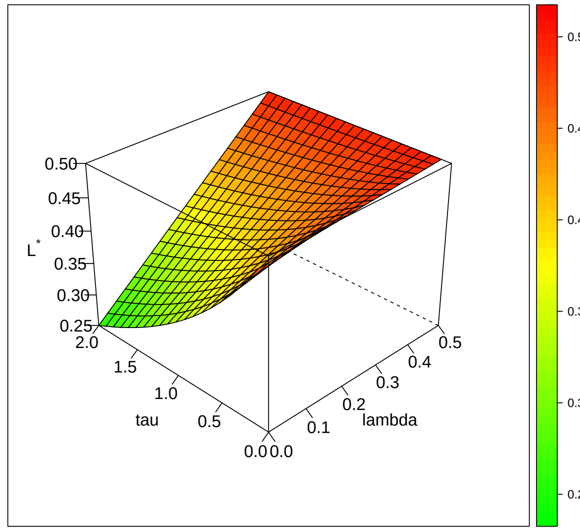


Panel C: $\alpha = 0.5$; $\gamma = 1$; $\sigma = 1$

Equilibrium price p^*

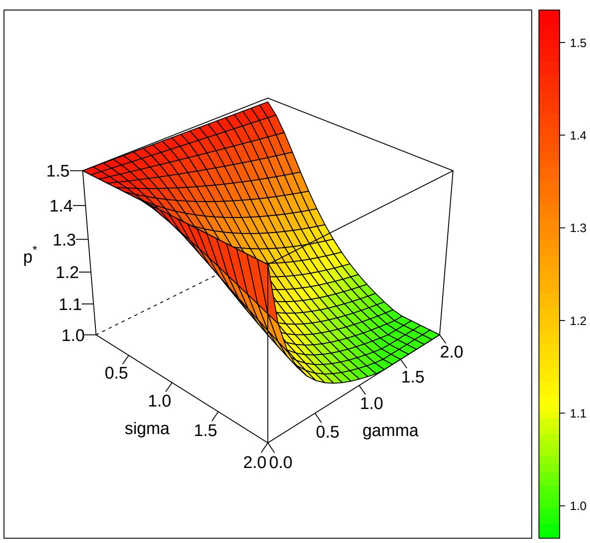


Equilibrium short-interest L^*



Panel D: $\alpha = 0.5$; $\tau = 0.5$; $\lambda = 0.1$

Equilibrium price p^*



Equilibrium short-interest L^*

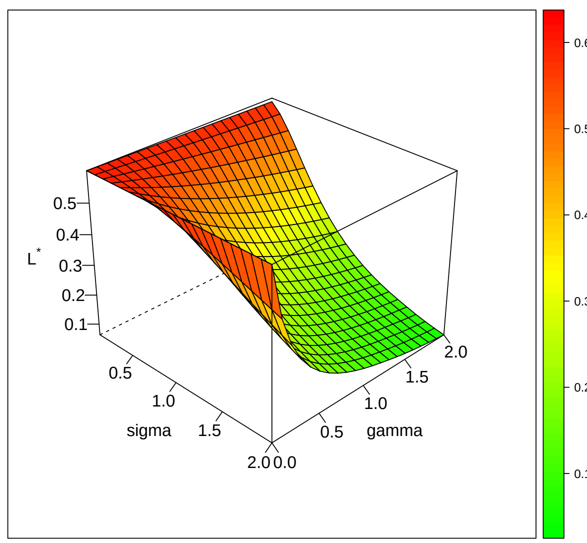
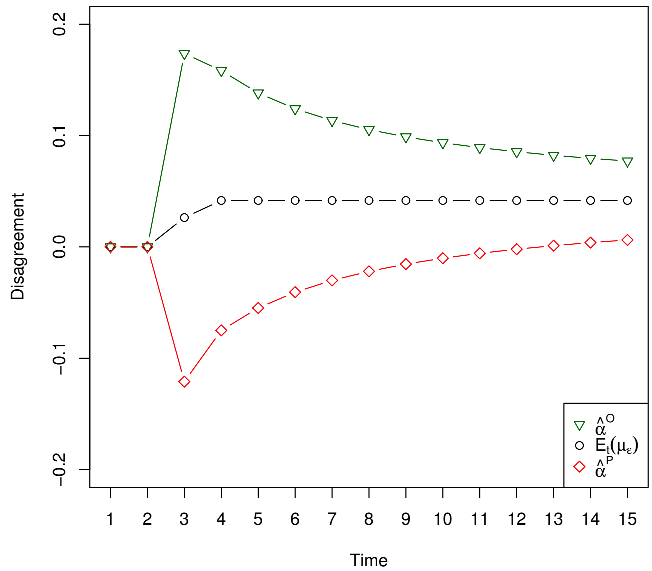


Figure 6: Numerical illustration of the dynamic model.
The upper panel shows the time series of the disagreement parameters $\hat{\alpha}_t^i$ and the expected value of μ_ϵ at time t. The lower panel shows the time series of the sum of realized fundamental shocks D_t, the equilibrium price p_t^* for several free lending supplies λ and the unbiased expected value of D_T at time t. All values are calculated for the model version with a optimist and a pessimist with equal risk aversion, see especially Equations (19) and (20). $\bar{\alpha}_1^O = \bar{\alpha}_1^P = 0$, $D_0 = 1$, $\zeta^2 = 0.25$, $\sigma^2 = 0.2$, $\gamma = 1$, $\sigma^2 = 1$ and $\tau = 2$. There is a disagreement shock in period 3 ($\bar{\alpha}_3^O = 0.2$, $\bar{\alpha}_3^P = -0.2$) and fundamental shocks in periods 3 and 4 ($\epsilon_3 = \epsilon_4 = 0.1$). There are no further disagreement shock. Fundamental shocks in periods 5 to 15 are all equal to the unbiased posterior belief in period 4, i.e., $\epsilon_t = 0.04\overline{6}\ \forall t \in [5, 15]$.



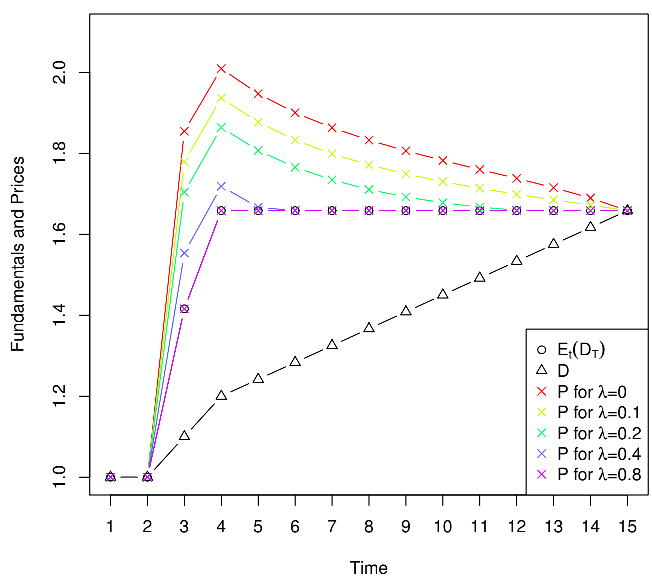


Figure 7: Cumulative log FF3-hedged return of overpriced winner portfolio over time.
We plot the cumulative FF3-hedged log-returns of the overpriced winner portfolio, i.e., stocks in the winner quintile, the quintile with the largest change in short-interest (conditional on being a winner) and in the lowest institutional ownership quintile (conditional on being a winner), over the first 10 years after portfolio formation. For each post-formation month, we first regress the time-series of observations on the three Fama and French factors. We then cumulate the log of the abnormal return (the alpha of the regression) over the 120 months. Additionally, we plot a confidence interval of the cumulated abnormal return by cumulating the upper/lower bound of the alpha estimates (estimate plus/minus 1.96 times the standard error).

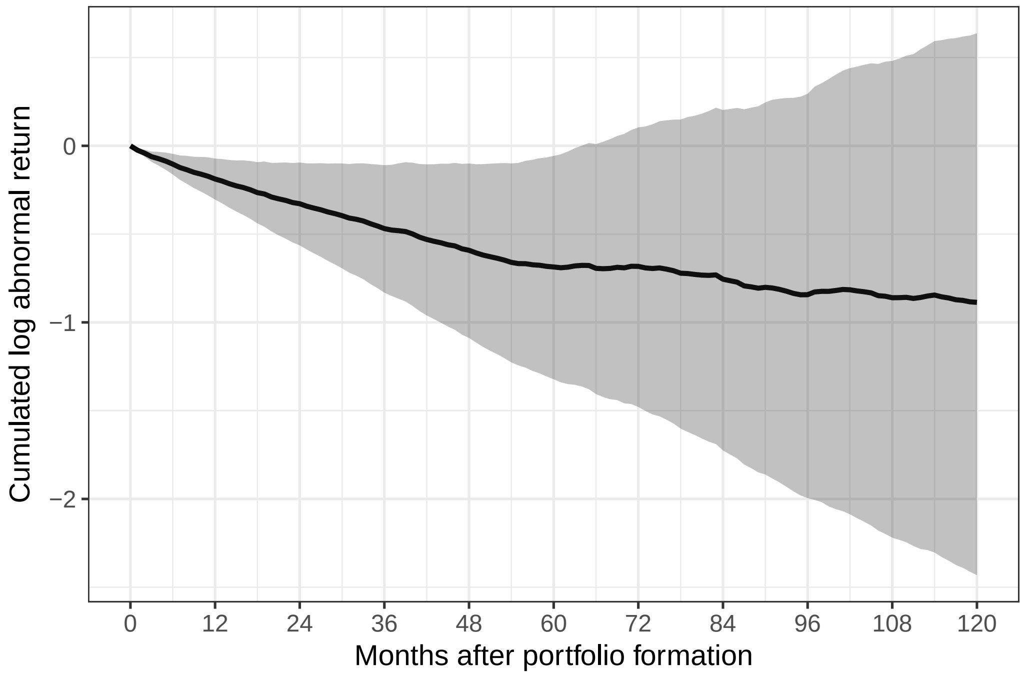


Figure 8: Earnings forecast dispersion of overpriced winner portfolio over time.
This figure shows the value-weighted average fiscal-year-end analyst earnings forecast dispersion of the overpriced winner portfolio from a 3x3x3 sort, i.e., stocks in the winner tercile, the tercile with the largest change in short-interest (conditional on being a winner) and in the lowest institutional ownership tercile (conditional on being a winner), from 1 year before until five years after portfolio formation.

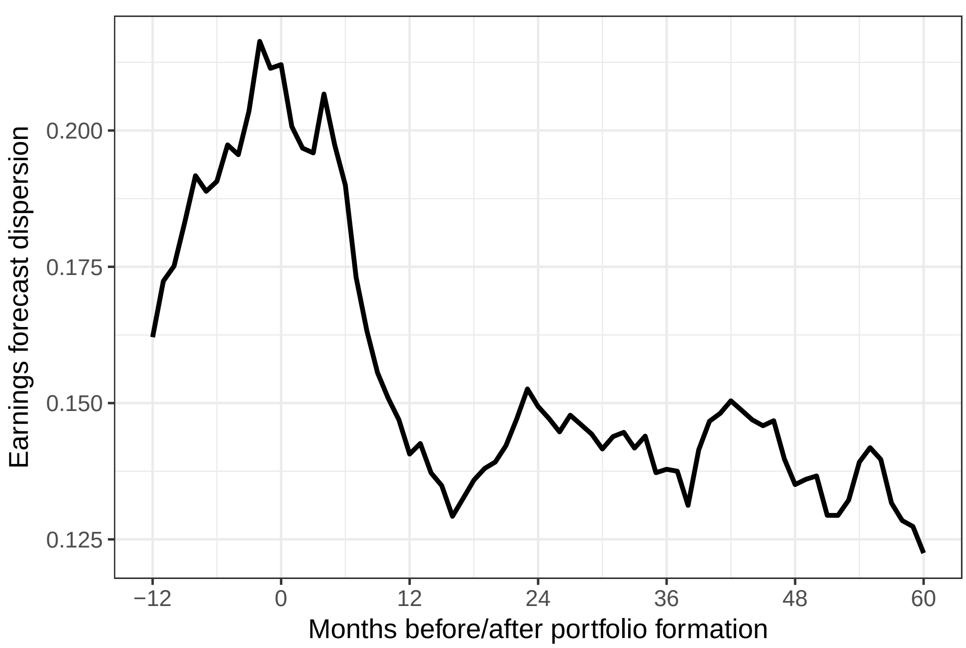


Figure 9: Cumulated return of different long-short portfolios.
The cumulated return of 1 dollar invested in June 1989 into different long-short portfolios is plotted over the whole sample period to December 2014. IVOL is calculated as in Ang, Hodrick, Xing, and Zhang (2006), WML is the standard Carhart (1997) momentum factor, MktRF, HML and SMB are the Fama and French (1993) factors and BAB is the betting-against-beta factor as in Frazzini and Pedersen (2014). BAW is the betting-against-winners portfolio that shorts the overpriced (high change in short interest and low institutional ownership) winners and goes long all other 24 winner portfolios (with equal weight on each portfolio but value-weighting within portfolios).

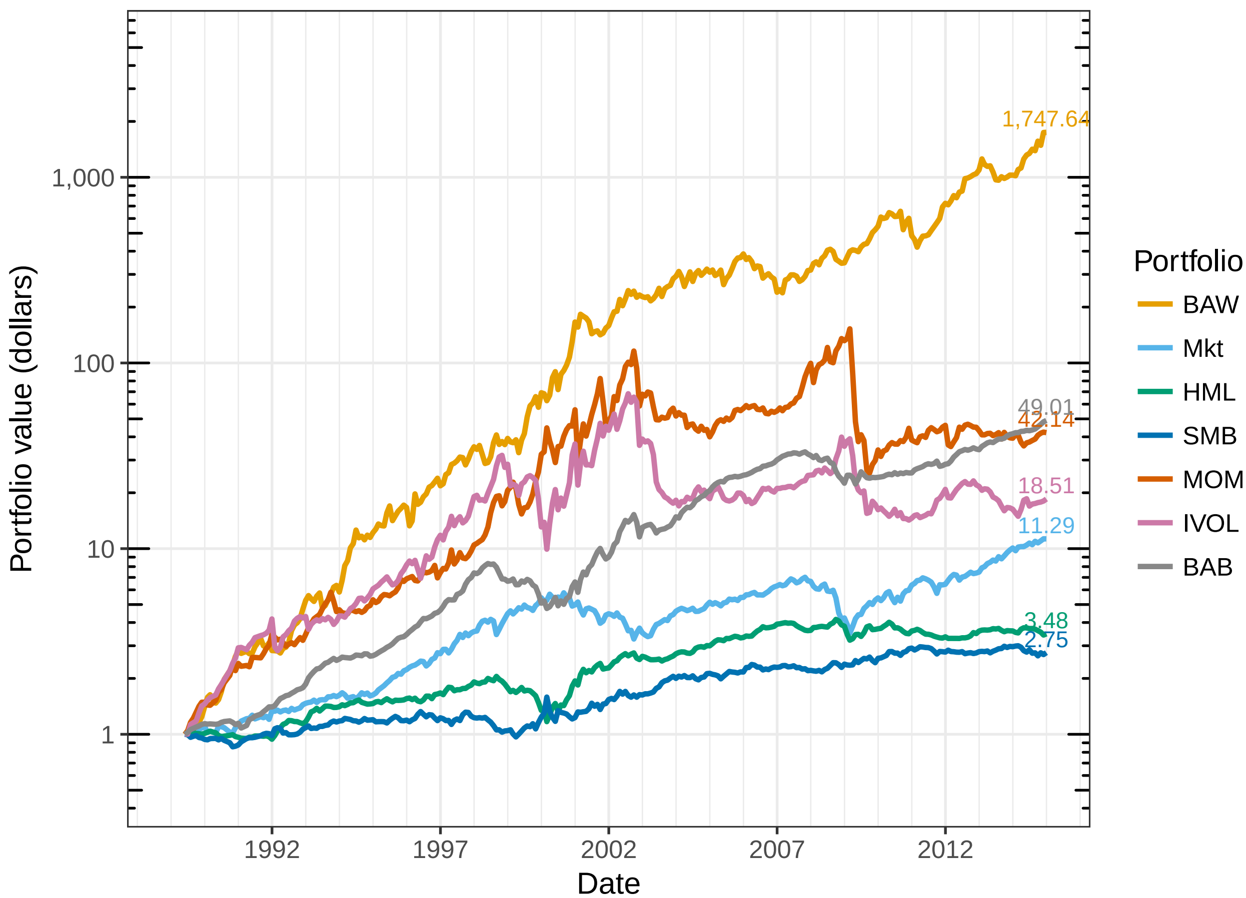


Figure 10: Average log excess returns around earnings announcements.
This figure shows average daily log excess returns of the constrained winners and the 24 other winner portfolio stocks around the day (t=0) of an earnings announcement that occurs in the month after portfolio formation. 95% confidence intervals are indicated in gray. To construct the figure, daily log excess returns are first centered around the day of announcement (t=0) and classified according to their portfolio membership of the previous three months. Stocks that were in the constrained winner portfolio in any of the three previous months are considered for the constrained winners. All remaining stocks that were in any other winner portfolio in one of the three previous months are considered for the other winners. We then calculate the average log excess return by portfolio and day relative to announcement. Stocks are weighted according to their share of market capitalization within their respective portfolio.

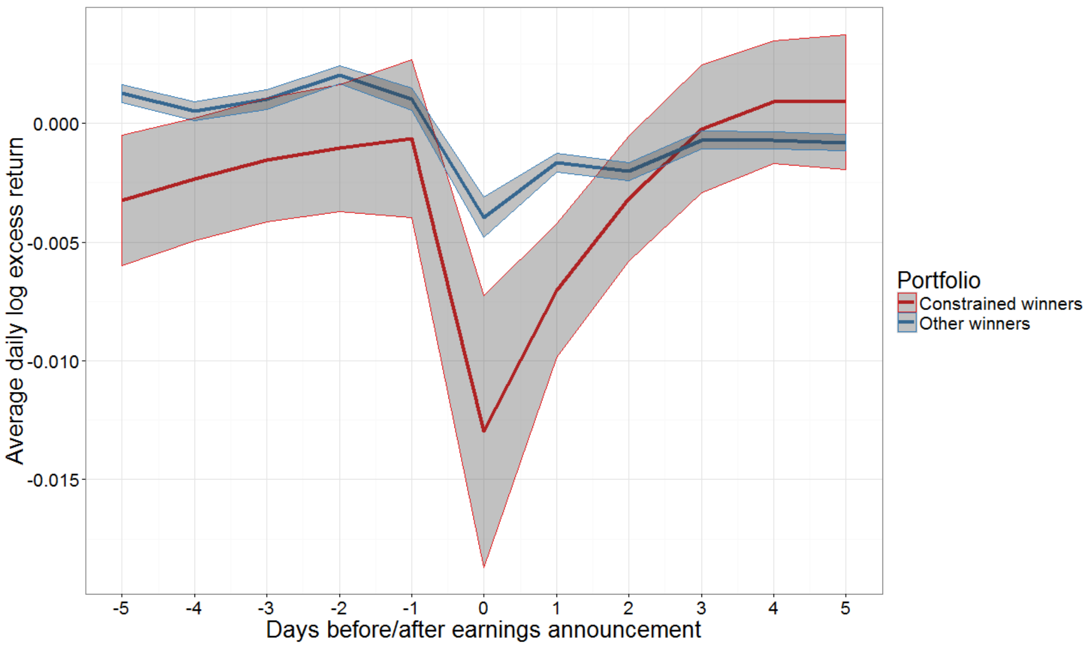
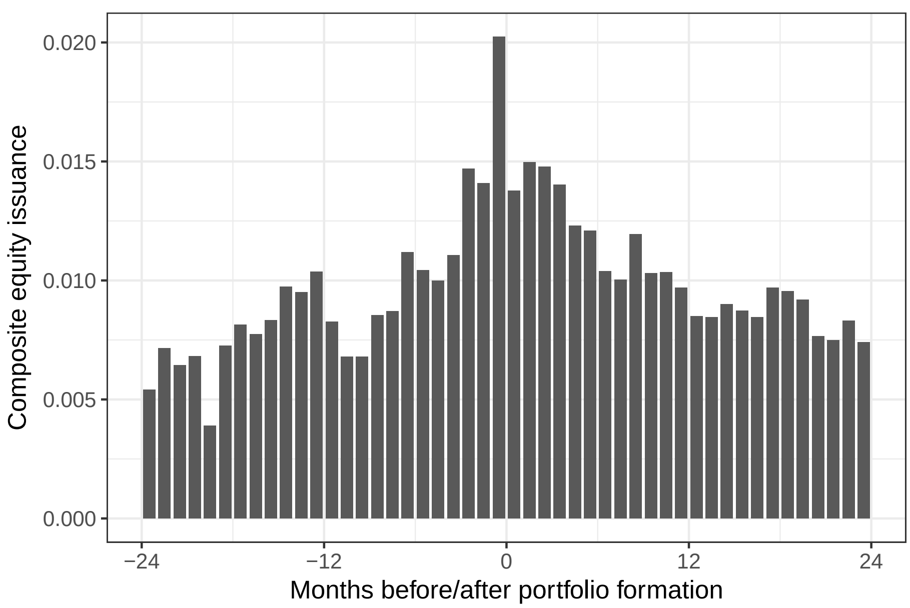


Figure 11: Composite equity issuance of constrained winners around portfolio formation.
Composite equity issuance as in Daniel and Titman (2006) is calculated for the constrained winner portfolio in the 24 months before and after portfolio formation (t=0). Stocks are weighted based on their previous month's market capitalization. The time-series average for each of these months relative to portfolio formation is displayed as a bar.



Tables

Table 1: Descriptive statistics of earnings forecast dispersion change sorted portfolios.
Stocks are sorted based on their past 1-year change in earnings forecast dispersion into 10 portfolios. The time-series average of the number of stocks in the portfolios is displayed in the first column. The next columns show the time series mean of monthly value-weighted portfolio averages of market equity in B$, return of the previous year (skipping the last month) in %, institutional ownership ratio (IOR), change in short-interest in PP, and SIRIO (short interest divided by institutional ownership) in %, all in the month of portfolio formation (t-1).

ΔEFD-Portfolio	Number of stocks	$MarketEquity_{t-1}$	$Return_{t-12-t-2}$	IOR_{t-1}	ΔSIR_{t-1}	$SIRIO_{t-1}$
1	227	14.63	15.38	63.31	-0.09	8.90
2	226	32.58	15.60	63.65	-0.25	11.31
3	226	56.95	16.36	62.35	-0.08	14.18
4	226	60.14	14.90	62.24	-0.10	6.84
5	226	68.80	13.80	61.73	-0.09	4.62
6	227	72.39	11.50	60.95	-0.07	4.84
7	226	65.96	8.66	61.26	0.08	7.01
8	226	50.08	4.33	61.28	0.17	10.49
9	226	26.37	-2.47	62.84	0.11	11.72
10	227	15.44	-9.87	62.42	0.36	10.35

Table 2: Fama-MacBeth regressions of future changes on past changes in earnings forecast dispersion.
The change in earnings forecast dispersion over the next year is regressed on positive (Column 1) and both positive and negative changes (column 2) in earnings forecast dispersion over the previous year in the cross-section of stocks in each month. Following the Fama and MacBeth (1973) procedure, the time-series average of the regression coefficients is presented. Standard errors are calculated following Newey and West (1987) with 11 lags. The time-series average of the cross-sectional R^2 is presented in the last row.

	(1)	(2)
Intercept	0.0761 (14.44)	0.0741 (14.23)
Positive change in disagreement (t-13 to t-1)	-0.8506 (-90.08)	-0.8492 (-89.51)
Negative change in disagreement (t-13 to t-1)		-0.0297 (-5.68)
R^2	0.3322	0.3332

Table 3: Excess returns of winner and loser portfolios.
This table contains monthly average excess returns of the 25 winner (Panel A) and 25 loser (Panel B) portfolios from a triple sort on the past 11-month return lagged by one month, institutional ownership and change in short interest over the past year. The second to last column presents the difference of low and high institutional ownership portfolios and the last column displays the alpha of that difference portfolio from a Fama-French three-factor regression. Similarly, the bottom two rows show the difference between high and low change in short-interest portfolios and the respective Fama-French three-factor alpha. Newey and West (1987) t-statistics are shown in parentheses.

Panel A: Winners

	Hi IOR	4	3	2	Lo IOR	Lo-Hi	FF3-α
Lo ΔSIR	1.07	0.74	1.49	1.02	0.58	-0.49 (-1.03)	-0.59 (-1.39)
2	1.07	0.87	0.42	1.50	0.46	-0.62 (-1.29)	-0.62 (-1.44)
3	1.04	1.10	0.80	1.01	0.87	-0.17 (-0.53)	-0.20 (-0.72)
4	1.09	0.71	1.05	1.24	0.48	-0.60 (-1.43)	-0.60 (-1.59)
Hi ΔSIR	1.05	0.94	0.89	0.51	-1.66	-2.71 (-5.03)	-2.76 (-5.28)
Hi-Lo	-0.02	0.20	-0.61	-0.51	-2.24		
t	(-0.09)	(0.61)	(-1.19)	(-0.84)	(-3.89)		
FF3-α	-0.16	0.13	-0.60	-0.61	-2.32		
t	(-0.68)	(0.42)	(-1.13)	(-1.21)	(-4.12)		

Panel B: Losers

	Hi IOR	4	3	2	Lo IOR	Lo-Hi	FF3-α
Lo ΔSIR	0.39	0.50	-0.19	-0.53	-0.96	-1.35 (-1.54)	-0.97 (-1.19)
2	0.91	0.67	0.30	-0.19	-1.08	-1.99 (-2.54)	-1.56 (-2.04)
3	-0.13	0.04	0.41	0.22	-0.09	0.04 (0.07)	0.34 (0.62)
4	-0.29	0.57	0.81	-0.63	-0.47	-0.17 (-0.27)	0.16 (0.27)
Hi ΔSIR	0.03	-0.28	-0.56	-1.65	-2.01	-2.08 (-2.29)	-2.08 (-2.22)
Hi-Lo	-0.36	-0.78	-0.37	-1.11	-1.05		
t	(-0.91)	(-1.46)	(-0.70)	(-1.68)	(-1.26)		
FF3-α	-0.24	-0.89	-0.54	-1.06	-1.29		
t	(-0.63)	(-1.59)	(-0.95)	(-1.52)	(-1.57)		

Table 4: Characteristics of triple sorted winner portfolios.
This table shows time-series averages of value-weighted mean characteristics of the 25 winner portfolios in the month of portfolio formation. Panel A displays the average number of stocks. Following are average market equity in billion US dollars (Panel B), return from month t-12 to the end of month t-2 in percent (Panel C), change in short interest from 11.5 months ago to 2 weeks ago in percentage points (Panel D), institutional ownership in percent of number of shares outstanding (Panel E), level of short interest two weeks prior to portfolio formation (Panel F), the ratio of book equity of the previous December to last month's market equity in percent (Panel G) and the average standard deviation of daily idiosyncratic returns in each portfolio (daily, in %) over the month prior to formation (Ang, Hodrick, Xing, and Zhang, 2006, Panel H). Panel I presents the ratio of short interest to institutional ownership (SIRIO) as in Drechsler and Drechsler (2016). The open-interest weighted average of differences in implied volatilities between matched put and call option pairs at month-end, as in Cremers and Weinbaum (2010) is shown in Panel J. Panels K and L show levels and changes over the preceding 12 months in turnover. Stock-level dispersion in analysts' fiscal-year-end earnings forecasts of winners and losers are calculated as the standard deviation of forecasts divided by the mean forecast in a given-month in %. Panel M features levels in the month of portfolio formation and Panel N shows the change over the preceding 12 months.

	Winners					Losers				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Panel A: Number of stocks										
Lo ΔSIR	54	45	31	22	13	40	38	34	27	16
2	22	28	33	39	42	27	31	32	34	30
3	16	24	32	43	51	13	21	30	39	48
4	34	37	36	30	27	28	32	33	33	32
Hi ΔSIR	54	38	32	26	16	66	38	24	17	11
Panel B: Average Market Equity (B$)										
Lo ΔSIR	12.34	25.68	32.30	14.94	6.52	5.04	8.94	1.51	1.13	0.16
2	15.48	36.87	40.04	20.81	2.76	8.13	15.62	8.38	0.91	0.43
3	13.47	34.60	40.46	20.65	1.72	6.76	21.30	8.93	1.72	0.49
4	14.58	31.65	26.71	9.95	1.89	10.46	23.26	13.12	0.56	0.90
Hi ΔSIR	8.20	10.59	20.50	5.55	2.33	4.64	13.95	2.69	1.01	0.33
Panel C: Formation Period Return (%)										
Lo ΔSIR	79	86	99	116	120	-38	-41	-44	-46	-49
2	70	70	81	90	105	-36	-38	-42	-44	-47
3	74	74	81	91	113	-36	-38	-41	-42	-45
4	74	77	90	113	151	-36	-38	-40	-43	-45
Hi ΔSIR	87	100	119	159	203	-38	-41	-44	-45	-47
Panel D: Change in Short-Interest over preceding year (PP)										
Lo ΔSIR	-3.79	-3.65	-3.78	-3.87	-7.33	-3.70	-3.85	-3.99	-4.08	-3.59
2	-0.42	-0.40	-0.38	-0.36	-0.32	-0.57	-0.54	-0.53	-0.51	-0.47
3	0.08	0.08	0.08	0.07	0.07	-0.05	-0.05	-0.04	-0.04	-0.05
4	0.78	0.72	0.72	0.72	0.71	0.46	0.39	0.41	0.37	0.33
Hi ΔSIR	4.66	3.87	4.19	4.89	6.44	4.11	3.77	3.79	4.19	3.39

Table 4: (continued)

	Winners					Losers				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Panel E: Institutional Ownership (%)										
Lo ΔSIR	80.13	62.91	47.75	28.94	11.21	75.57	48.83	29.53	15.22	4.38
2	79.62	61.17	44.17	24.81	7.87	73.27	48.76	28.30	13.63	3.93
3	78.79	60.50	42.61	23.48	7.45	71.82	47.04	28.79	13.10	3.53
4	78.97	61.94	44.15	24.70	7.95	72.49	48.85	29.36	13.74	5.10
Hi ΔSIR	82.24	61.47	42.75	24.50	8.91	75.41	49.65	30.33	15.91	5.93
Panel F: Level of Short-interest (%)										
Lo ΔSIR	4.76	3.57	3.47	3.43	5.94	4.69	4.16	4.24	4.21	1.91
2	2.81	1.55	1.37	1.11	0.78	2.84	1.77	1.81	1.22	0.74
3	2.72	1.44	1.18	0.87	0.52	2.07	1.11	0.82	0.43	0.24
4	3.67	2.61	2.23	2.02	1.66	2.76	1.92	1.94	1.56	1.00
Hi ΔSIR	9.58	7.35	7.22	7.62	9.47	8.26	7.63	7.74	7.11	5.53
Panel G: Book-to-market ratio (%)										
Lo ΔSIR	29	30	29	27	26	77	92	90	79	79
2	33	37	38	38	23	78	90	95	92	78
3	32	37	40	38	25	87	102	122	99	81
4	31	33	34	30	24	83	98	120	95	77
Hi ΔSIR	29	30	28	22	18	88	96	101	90	72
Panel H: Idiosyncratic volatility (%, daily)										
Lo ΔSIR	1.77	1.75	1.95	2.43	3.05	2.62	3.08	3.70	4.27	5.71
2	1.63	1.60	1.85	2.32	3.10	2.40	2.96	3.72	4.44	5.74
3	1.63	1.62	1.90	2.30	3.11	2.61	2.96	4.06	4.83	5.99
4	1.66	1.66	1.87	2.45	3.43	2.37	2.85	3.48	4.43	5.85
Hi ΔSIR	1.91	2.03	2.31	2.88	3.70	2.52	2.89	3.61	4.28	5.82
Panel I: SIRIO (%)										
Lo ΔSIR	5.24	5.52	8.33	16.17	120.09	5.96	10.83	20.74	38.62	105.41
2	3.10	2.31	2.96	4.25	32.61	3.66	3.60	7.07	12.25	60.85
3	3.02	2.19	2.43	3.30	17.26	2.65	2.21	2.82	3.93	25.00
4	4.14	3.98	5.04	8.85	71.84	3.48	3.76	6.80	12.45	79.09
Hi ΔSIR	10.61	11.89	19.16	45.18	238.34	10.35	18.17	34.57	69.32	327.57
Panel J: Option volatility spread (%)										
Lo ΔSIR	-0.84	-0.75	-0.98	-1.20	-2.88	-0.71	-0.56	-1.42	-3.79	-2.87
2	-0.63	-0.55	-0.61	-1.21	-2.32	-0.28	-0.13	-0.61	-2.47	-5.80
3	-0.77	-0.49	-0.49	-1.18	-2.47	-0.52	0.76	-2.25	-2.88	-11.39
4	-0.63	-0.59	-0.81	-0.93	-0.45	0.04	-0.42	-1.97	-3.91	-5.83
Hi ΔSIR	-0.91	-1.11	-1.57	-2.44	-5.29	-1.09	-1.12	-3.82	-6.27	-4.64

Table 4: (continued)

	Winners					Losers				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Panel K: Turnover (%)										
Lo ΔSIR	2.42	2.20	2.31	2.29	1.64	2.71	2.33	1.80	1.52	1.51
2	1.89	1.50	1.40	1.02	0.88	2.31	1.84	1.31	0.97	1.03
3	1.91	1.47	1.32	1.07	0.77	2.25	1.65	1.25	0.80	0.69
4	2.11	1.79	1.55	1.50	1.58	2.16	1.94	1.61	1.03	1.07
Hi ΔSIR	3.13	2.82	2.89	3.05	4.55	3.23	3.09	2.57	1.98	2.94
Panel L: Change in turnover over preceding year (PP)										
Lo ΔSIR	-0.17	-0.25	-0.08	0.09	0.27	-0.27	-0.81	-1.06	-1.52	-1.61
2	0.04	0.02	-0.05	0.21	0.25	0.10	-0.08	-0.34	-0.49	-0.56
3	0.25	0.11	0.27	0.37	0.35	0.20	0.17	-0.28	-0.35	-0.19
4	0.25	0.26	0.37	0.63	0.86	0.34	0.21	0.16	-0.14	-0.13
Hi ΔSIR	0.80	0.89	1.06	1.75	3.38	0.73	0.45	0.21	-0.07	0.73
Panel M: Level of forecast dispersion (%)										
Lo ΔSIR	8.74	8.43	12.27	14.88	21.95	21.33	28.76	32.05	37.67	32.90
2	7.85	7.52	9.14	11.83	21.91	21.99	28.59	37.02	32.77	35.04
3	7.10	6.97	9.66	11.65	14.16	21.93	32.43	41.56	36.97	38.37
4	7.27	6.61	10.01	17.13	14.58	23.08	24.47	33.16	41.02	38.00
Hi ΔSIR	9.41	10.26	14.56	22.15	35.31	25.16	31.54	42.03	40.69	33.40
Panel N: Change in forecast dispersion over preceding year (PP)										
Lo ΔSIR	-3.90	-4.40	-1.30	-3.39	-4.66	9.69	6.75	3.45	12.36	15.83
2	-3.37	-3.04	-1.86	-3.97	4.98	8.72	12.18	11.06	10.29	5.63
3	-1.98	-3.86	-2.94	-4.90	-3.42	9.42	17.72	17.92	8.64	10.43
4	-2.52	-4.18	-3.74	-9.01	1.71	12.12	10.93	11.41	12.60	11.27
Hi ΔSIR	-5.50	-3.11	-8.63	1.00	15.50	14.76	15.93	21.37	15.13	12.56

Table 5: Explaining the returns with conventional factors.
We regress monthly returns to a portfolio going short low institutional ownership, high change in short-interest winners and long all other winner portfolios ("Betting Against Winners", BAW, Panel A) on different long-short portfolio returns. Panel B repeats the exercise with the excess-return of the short-side of the BAW portfolio and Panel C uses the low IOR, high change in short-interest losers as the left-hand-side portfolio. Column (1) shows the raw average of that strategy, column (2) displays results from a CAPM regression on the market excess return. Column (3) represents results from a Fama and French (1993) 3-factor regression. In column (4), we add the Carhart (1997) momentum-factor, and in column (5), IVOL as in Ang, Hodrick, Xing, and Zhang (2006) is included. Columns (6), (7) and (8) add the Pastor and Stambaugh (2003) liquidity factor, a short-term reversal portfolio and the CME factor based on short interest over institutional ownership from Drechsler and Drechsler (2016), respectively. Column (9) includes all of the aforementioned. Newey and West (1987) t-statistics are shown in parentheses.

Panel A: Excess returns of the "Betting Against Winners" portfolio									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	2.57	2.79	2.71	2.65	2.56	2.66	2.68	1.82	1.86
	(5.45)	(5.66)	(5.77)	(5.84)	(5.94)	(5.69)	(5.89)	(4.29)	(4.20)
MktRF		-0.33	-0.22	-0.20	-0.16	-0.19	-0.15	0.01	0.03
		(-2.76)	(-2.00)	(-1.91)	(-1.59)	(-1.92)	(-1.33)	(0.12)	(0.28)
HML			0.29	0.31	0.23	0.30	0.31	-0.12	-0.10
			(1.44)	(1.48)	(1.22)	(1.44)	(1.59)	(-0.54)	(-0.50)
SMB			-0.46	-0.46	-0.31	-0.46	-0.44	-0.12	-0.12
			(-3.41)	(-3.55)	(-1.59)	(-3.58)	(-3.33)	(-0.72)	(-0.56)
MOM				0.03	-0.00	0.03	0.01	-0.04	-0.04
				(0.62)	(-0.00)	(0.62)	(0.35)	(-0.90)	(-0.84)
IVOL					-0.09				0.01
					(-1.22)				(0.07)
LIQ						-0.02			-0.01
						(-0.16)			(-0.11)
REV							-0.21		-0.12
							(-1.30)		(-0.76)
CME								0.63	0.62
								(4.70)	(4.38)
R^2	0.0000	0.0256	0.0738	0.0716	0.0730	0.0686	0.0749	0.1327	0.1263

Table 5: (continued)

Panel B: Excess returns of low IOR, high ΔSIR winners									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-1.66	-2.56	-2.47	-2.81	-2.59	-2.81	-2.84	-1.88	-1.89
	(-2.55)	(-4.47)	(-4.92)	(-5.84)	(-5.84)	(-5.74)	(-5.88)	(-4.27)	(-3.90)
MktRF		1.41	1.17	1.30	1.22	1.30	1.25	1.07	1.02
		(9.06)	(10.00)	(11.72)	(11.40)	(11.24)	(11.01)	(11.92)	(8.00)
HML			-0.45	-0.37	-0.21	-0.38	-0.38	0.09	0.12
			(-2.11)	(-1.66)	(-1.04)	(-1.73)	(-1.68)	(0.40)	(0.60)
SMB			1.16	1.14	0.82	1.14	1.12	0.77	0.62
			(7.47)	(8.12)	(4.03)	(7.96)	(7.90)	(4.87)	(3.10)
MOM				0.16	0.22	0.16	0.17	0.23	0.26
				(3.26)	(4.43)	(3.19)	(3.73)	(4.83)	(4.96)
IVOL					0.21				0.11
					(2.42)				(1.39)
LIQ						-0.01			-0.02
						(-0.05)			(-0.16)
REV							0.26		0.19
							(1.53)		(1.15)
CME								-0.69	-0.61
								(-5.12)	(-3.87)
R^2	0.0000	0.2887	0.4374	0.4538	0.4647	0.4519	0.4578	0.4956	0.4964

Table 5: (continued)

Panel C: Excess returns of low IOR, high ΔSIR losers									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-2.01	-3.07	-3.18	-2.13	-1.11	-2.14	-2.17	-0.77	-0.52
	(-1.87)	(-3.38)	(-4.07)	(-2.37)	(-1.49)	(-2.46)	(-2.40)	(-0.86)	(-0.70)
MktRF		1.63	1.47	1.06	0.69	1.06	0.99	0.73	0.48
		(7.54)	(6.78)	(7.10)	(3.80)	(6.93)	(5.09)	(3.61)	(2.68)
HML			0.10	-0.14	0.58	-0.13	-0.15	0.55	0.88
			(0.24)	(-0.40)	(1.52)	(-0.38)	(-0.42)	(1.73)	(2.24)
SMB			1.22	1.27	-0.18	1.27	1.24	0.72	-0.36
			(3.35)	(3.93)	(-0.50)	(3.83)	(3.91)	(2.00)	(-0.87)
MOM				-0.49	-0.22	-0.49	-0.47	-0.39	-0.17
				(-3.55)	(-1.61)	(-3.51)	(-3.31)	(-2.85)	(-1.36)
IVOL					0.92				0.83
					(4.80)				(3.85)
LIQ						0.03			0.03
						(0.10)			(0.13)
REV							0.36		0.28
							(1.03)		(1.10)
CME								-1.02	-0.55
								(-4.04)	(-1.78)
R^2	0.0000	0.1448	0.1852	0.2511	0.3455	0.2485	0.2526	0.2846	0.3525

Table 6: Composite equity issuance from 3 months before to 3 months after portfolio formation. This table shows time-series averages of the value-weighted composite equity issuance measure of the 25 winner portfolios around the month of portfolio formation. The composite equity issuance measure of a firm is the part of the change in a firm's market capitalization that cannot be explained by a firm's stock return. It is calculated over a six-month horizon, starting three months prior to portfolio formation and ranging to three months after portfolio formation.

Winners						
	Hi IOR	4	3	2	Lo IOR	Lo-Hi
Lo ΔSIR	1.97	2.05	3.67	5.94	8.09	6.07 (5.29)
2	0.60	0.22	1.31	2.12	5.66	5.14 (5.70)
3	0.59	0.04	1.44	1.58	5.87	5.34 (5.98)
4	0.92	1.13	2.09	4.00	8.30	7.40 (9.70)
Hi ΔSIR	4.21	4.06	5.53	7.70	12.85	8.61 (7.43)
Hi-Lo	2.24	2.01	1.86	1.76	5.03	
t	(3.75)	(3.18)	(2.96)	(1.86)	(4.16)	

Online Appendix for Overpriced Winners

A Model: Who Gains and Who Loses When Divergence-of-Opinion is Resolved?

In the baseline model, the pessimist's gain or loss is equal to her shorting demand times the gain or loss from shorting:

$$Losses_{Pessimist} = \frac{V\,(1+\alpha) - p^*}{\gamma\sigma^2} \cdot \left[\left(1 + \frac{c^*}{2} - c^*\right) - 1\right] = \frac{\alpha\, V - \frac{c^*}{2}}{\gamma\sigma^2} \cdot \left[\frac{-c^*}{2}\right] < 0 \tag{A.1}$$

Analogously, we can calculate the gains or losses of the optimist as

$$Losses_{Optimist} = \frac{p^* - (V(1-\alpha)) - c^*}{\gamma\sigma^2} \cdot \left[1 - \left(1 + \frac{c^*}{2}\right)\right] = \frac{\alpha\, V - \frac{c^*}{2}}{\gamma\sigma^2} \cdot \left[\frac{-c^*}{2}\right] < 0 \tag{A.2}$$

Stock supply and stock demand are equal in equilibrium, so both groups lose the same amount of money, in aggregate. Adding both losses up yields $\left(\frac{\alpha\, V - \frac{c^*}{2}}{\gamma\sigma^2}\right)(-c^*)$. In our example parameterization, both groups lose 0.06 each, the half of the total search costs caused by shorting. The losses of the speculators are the gains of the security lenders as

$$Gains_{Lenders} = L^* c^* = \left(\frac{\alpha\, V - \frac{c^*}{2}}{\gamma\sigma^2}\right)(c^*) \tag{A.3}$$

B Model Extension: A Mass of Risk-Averse Speculators with Varying Attention

We assume in this Appendix that there is a unit mass of speculators with divergent beliefs about the payoff of the stock: The speculators' beliefs about the stock's final payoff are uniformly distributed on the interval $[V(1-\alpha), V(1+\alpha)]$, with $\alpha > 0$, where α is a measure of their divergence-of-opinion. That is, the density function of beliefs is given by

$$f(\theta) = \begin{cases} 0 & \text{if } \theta < V(1-\alpha) \\ \frac{1}{2\alpha} & \text{if } V(1-\alpha) \leq \theta \leq V(1-\alpha) \\ 0 & \text{if } \theta > V(1-\alpha) \end{cases} \tag{B.1}$$

where θ represents the speculators' private valuation of the stock and

$$F(\theta) = \begin{cases} 0 & \text{if } \theta < V(1-\alpha) \\ \frac{\theta-(V(1-\alpha))}{2\alpha} & \text{if } V(1-\alpha) \leq \theta \leq V(1-\alpha) \\ 1 & \text{if } \theta > V(1-\alpha) \end{cases} \tag{B.2}$$

is the corresponding cumulative density function. Speculators are always right on average, in that the average expected payoff $\int_{-\infty}^{\infty} \theta f(\theta)\, d\theta = V$, is equal to the rationally expected payoff, but half of the speculators are "optimists" and half are "pessimists."

The optimization problem of an individual speculator stays the same as in the baseline model. The investor demands $\frac{V(1+\alpha)-p}{\gamma\sigma^2}$ if he is a long investor and his short demand is equal to $\frac{p-(V(1-\alpha))-c}{\gamma\sigma^2}$ if he is a short investor. Optimists and pessimists will enter the demand or supply side of the stock market with a demand or supply of 2δ times their measure. Intuitively, δ can be thought of as capturing the quantity of speculators in the economy: a high δ can reflect the presence of a large number of speculators who are willing to put their amounts of capital at risk in betting on this stock. Integrating over the mass of speculators yields demand

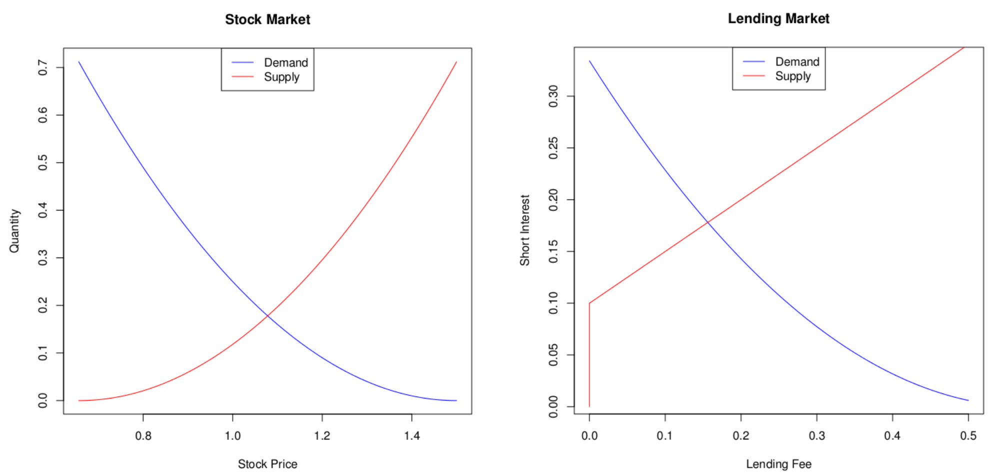
$$S^d(p) = \frac{2\delta}{2\alpha V} \int_p^{V(1+\alpha)} \frac{\theta - p}{\gamma\sigma^2}\, d\theta = \frac{\delta}{2\alpha V \gamma\sigma^2} \left((V(1+\alpha)) - p\right)^2 \tag{B.3}$$

and supply on the stock market

$$S^S(p) = \frac{2\delta}{2\alpha V} \int_{V(1-\alpha)}^{p-c} \frac{p - \theta - c}{\gamma\sigma^2}\, d\theta = \frac{\delta}{2\alpha V \gamma\sigma^2} \left((p-c) - (V(1-\alpha))\right)^2 \tag{B.4}$$

Figure B.1 shows an example for the parameters α=0.5, V=1, λ=0.1, σ=1, γ=1, δ=1 and τ=2. Demand and supply on the stock market are now quadratic functions of the price. The supply on the lending market is unchanged compared to the baseline model.

Figure B.1: Supply and demand in the stock and the lending market (extended model): This figure shows the supply and demand functions in both the stock (Panel A) and the lending market (Panel B) for α=0.5, V=1, λ=0.1, σ=1, γ=1, δ=1 and τ=2. In Panel A (Panel B), we draw supply and demand curves assuming that c (p) stays constant if p (c) is varied. Market clearing occurs at their respective intersections.



Market clearing on both markets yields the equilibrium quantities:

$$c^* = \frac{1}{\delta\tau}\left(2\alpha\delta\tau V + 4\gamma\alpha\sigma^2 V - \sigma\sqrt{8\gamma\alpha V(2\alpha\delta\tau V + 2\gamma\alpha\sigma^2 V + \delta\lambda\tau^2)}\right) \tag{B.5}$$

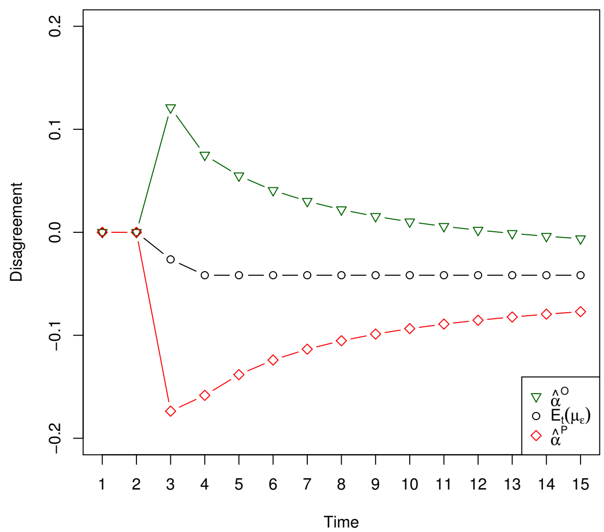
$$p^* = V + \frac{c^*}{2} \tag{B.6}$$

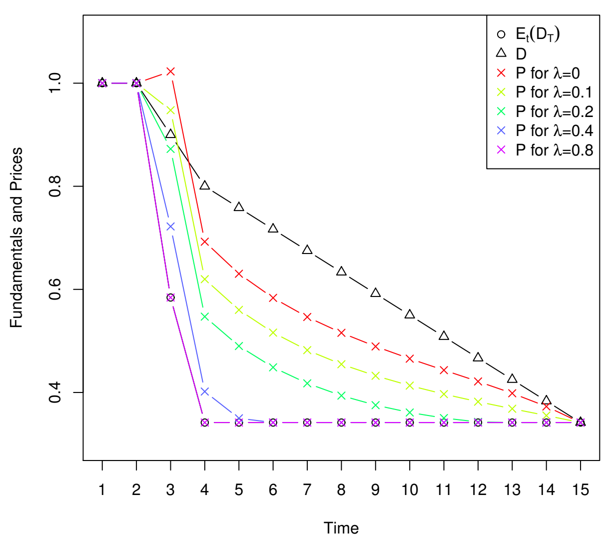
$$L^* = \lambda + \frac{1}{\tau}c^* \tag{B.7}$$

The attention measure δ and risk aversion γ are substitutes in this model. Both parameters govern simultaneously the speculative demand of the stock and therefore potential mispricing in equilibrium. High speculative demand could be caused either by high attention, low risk aversion, or a combination of both. Interestingly, if risk aversion approaches 0, i.e., speculators approach risk neutrality, equilibrium quantities are the same in the baseline and the extended model: $\lim_{\gamma\to 0} L^* = \lambda + \frac{1}{\tau}c^* = \lambda + \frac{2\alpha V}{\tau}$, $\lim_{\gamma\to 0} c^* = 2\alpha V$ and $\lim_{\gamma\to 0} p^* = V(1+\alpha)$. We obtain these quantities once more if attention δ goes towards infinity in the extended model: $\lim_{\delta\to\infty} L^* = \lambda + \frac{1}{\tau}c^* = \lambda + \frac{2\alpha V}{\tau}$, $\lim_{\delta\to\infty} c^* = 2\alpha V$ and $\lim_{\delta\to\infty} p^* = V(1+\alpha)$.

C Predictions of Dynamic Model: Negative Fundamental Shocks

Figure C.1: Numerical illustration of the dynamic model: The upper panel shows the time series of the disagreement parameters $\hat{\alpha}_t^i$ and the expected value of μ_ϵ at time t. The lower panel shows the time series of the sum of realized fundamental shocks D_t, the equilibrium price p_t^* for several free lending supplies λ and the unbiased expected value of D_T at time t. All values are calculated for the model version with a optimist and a pessimist with equal risk aversion, see especially Equations (19) and (20). $\bar{\alpha}_1^O = \bar{\alpha}_1^P = 0$, $D_0 = 1$, $\zeta^2 = 0.25$, $\sigma^2 = 0.2$, $\gamma = 1$, $\sigma^2 = 1$ and $\tau = 2$. There is a disagreement shock in period 3 ($\bar{\alpha}_3^O = 0.2$, $\bar{\alpha}_3^P = -0.2$) and fundamental shocks in periods 3 and 4 ($\epsilon_3 = \epsilon_4 = -0.1$). There are no further disagreement shock. Fundamental shocks in periods 5 to 15 are all equal to the unbiased posterior belief in period 4, i.e., $\epsilon_t = -0.04\bar{6}\ \forall t \in [5, 15]$.





D Additional Tables

Table D.1: Excess returns of all portfolios except winners and losers.
Shown are monthly average excess returns of the 75 middle portfolios from a triple sort on the past 11-month return lagged by one month, institutional ownership and change in short interest over the past year (see Table 3 for winners and losers). The second to last column presents the difference of low and high institutional ownership portfolios and the last column displays the alpha of that difference portfolio from a Fama-French three-factor regression. Similarly, the bottom two rows show the difference between high and low change in short-interest portfolios and the respective Fama-French three-factor alpha. Panel A presents the moderate losers, and Panels B present the middle quantile of the momentum sort and Panel C contains the moderate winners. Newey and West (1987) t-statistics are shown in parentheses.

Panel A: Moderate Losers (2^{nd} momentum quintile)							
	Hi IOR	4	3	2	Lo IOR	Lo–Hi	FF3-a
Lo ΔSIR	0.56	0.82	0.87	0.58	0.15	-0.41 (-0.77)	-0.36 (-0.70)
2	0.82	0.59	0.93	0.85	0.55	-0.28 (-0.60)	-0.18 (-0.34)
3	0.47	0.96	0.09	0.54	0.71	0.23 (0.58)	0.47 (0.99)
4	0.55	0.58	0.40	0.30	-0.18	-0.72 (-1.63)	-0.57 (-1.28)
Hi ΔSIR	0.34	0.33	0.14	0.07	0.14	-0.20 (-0.32)	0.02 (0.03)
Hi–Lo	-0.22	-0.49	-0.73	-0.52	-0.01		
t	(-1.15)	(-1.92)	(-1.78)	(-1.24)	(-0.01)		
FF3-a	-0.29	-0.52	-0.86	-0.33	0.08		
t	(-1.51)	(-2.33)	(-2.15)	(-0.78)	(0.11)		

Panel B: Middle Portfolio (3^{nd} momentum quintile)							
	Hi IOR	4	3	2	Lo IOR	Lo–Hi	FF3-a
Lo ΔSIR	0.77	0.54	1.01	0.60	-0.04	-0.81 (-2.22)	-0.74 (-1.85)
2	0.75	0.79	0.68	0.95	0.52	-0.22 (-0.55)	-0.04 (-0.12)
3	0.74	0.82	0.53	0.75	0.51	-0.23 (-0.65)	0.01 (0.02)
4	0.57	0.60	0.55	0.61	0.81	0.24 (0.62)	0.41 (1.01)
Hi ΔSIR	0.55	0.73	0.41	0.44	-0.44	-0.99 (-2.00)	-0.84 (-1.78)
Hi–Lo	-0.22	0.20	-0.60	-0.15	-0.40		
t	(-1.21)	(0.72)	(-2.28)	(-0.47)	(-0.75)		
FF3-a	-0.29	0.15	-0.71	-0.09	-0.40		
t	(-1.84)	(0.63)	(-2.56)	(-0.31)	(-0.71)		

Table D.1, continued:

Panel C: Moderate Winners (4th momentum quintile)							
	Hi IOR	4	3	2	Lo IOR	Lo–Hi	FF3-a
Lo ΔSIR	0.77	0.63	0.99	0.88	0.87	0.10 (0.21)	0.21 (0.51)
2	0.65	0.79	1.00	0.97	1.37	0.72 (2.05)	0.94 (2.89)
3	0.89	0.93	0.87	1.15	0.94	0.05 (0.14)	0.28 (0.73)
4	0.87	0.82	0.63	0.82	0.94	0.06 (0.17)	0.11 (0.32)
Hi ΔSIR	0.76	0.95	0.73	0.52	0.11	-0.65 (-1.26)	-0.58 (-1.34)
Hi–Lo	-0.01	0.32	-0.26	-0.36	-0.76		
t	(-0.08)	(1.36)	(-1.22)	(-0.97)	(-1.44)		
FF3-a	-0.04	0.32	-0.35	-0.43	-0.84		
t	(-0.23)	(1.44)	(-1.73)	(-1.27)	(-1.64)		

E Robustness Checks

Table E.1: Excess returns of winner portfolios with conditional sorting. This table contains monthly average excess returns of the 25 winner portfolios from first, a triple sort on the past 11-month return lagged by one month, then conditional on that, a sort on institutional ownership and, again conditioning on the latter, a sort on change in short interest over the past year. The second to last column presents the difference of low and high institutional ownership portfolios and the last column displays the alpha of that difference portfolio from a Fama-French three-factor regression. Similarly, the bottom two rows show the difference between high and low change in short-interest portfolios and the respective Fama-French three-factor alpha. Newey and West (1987) t-statistics are shown in parentheses.

	Hi IOR	4	3	2	Lo IOR	Lo–Hi	FF3-a
Lo ΔSIR	1.17	0.73	1.37	1.18	0.34	-0.83 (-1.91)	-0.95 (-2.58)
2	1.01	0.85	0.45	1.67	0.65	-0.36 (-0.90)	-0.35 (-0.95)
3	1.13	0.92	0.95	1.01	0.46	-0.67 (-1.44)	-0.60 (-1.52)
4	1.02	0.87	1.08	1.21	0.29	-0.73 (-1.71)	-0.61 (-1.41)
Hi ΔSIR	1.02	0.81	0.75	0.45	-0.56	-1.59 (-3.54)	-1.64 (-3.77)
Hi–Lo	-0.14	0.08	-0.62	-0.72	-0.90		
t	(-0.55)	(0.23)	(-1.34)	(-1.48)	(-2.06)		
FF3-a	-0.32	0.04	-0.57	-0.80	-1.02		
t	(-1.08)	(0.13)	(-1.16)	(-1.75)	(-2.07)		

Table E.2: Characteristics of conditionally triple sorted winner portfolios: This table shows time-series averages of value-weighted mean characteristics of the 25 winner portfolios in the month of portfolio formation. Panel A displays the average number of stocks. Following are average market equity in billion US dollars (Panel B), return from month t-12 to the end of month t-2 in percent (Panel C), change in short interest from 11.5 months ago to 2 weeks ago in percentage points (Panel D), institutional ownership in percent of number of shares outstanding (Panel E), level of short interest prior to portfolio formation (Panel F), the ratio of book equity of the previous December to last month's market equity in percent (Panel G) and the previous month's idiosyncratic volatility as in Ang, Hodrick, Xing, and Zhang (2006) in percent (Panel H).

	Panel A: Number of Stocks					Panel B: Average Market Equity				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	36	35	33	32	30	10.28	23.38	35.22	18.66	7.32
2	36	34	32	31	29	15.97	34.78	34.96	20.75	1.46
3	36	34	33	32	31	15.98	40.33	42.40	13.95	0.36
4	36	34	32	32	30	11.93	27.72	26.05	12.26	1.29
Hi ΔSIR	36	35	33	32	30	6.54	10.44	20.89	6.21	2.44

	Panel C: Formation Period Return					Panel D: Change in Short-Interest				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	83.68	89.48	94.98	110.23	113.39	-5.43	-4.69	-3.50	-3.25	-5.55
2	70.59	72.74	81.38	87.84	101.35	-0.95	-0.75	-0.37	-0.18	-0.03
3	72.77	72.68	81.70	94.37	109.85	0.14	-0.00	0.11	0.09	0.03
4	77.95	78.58	88.47	109.52	133.00	1.42	0.79	0.78	0.58	0.26
Hi ΔSIR	91.45	100.77	116.21	146.22	185.40	6.46	3.97	4.16	4.11	4.78

	Panel E: Institutional Ownership					Panel F: Level of Short-interest				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	83.29	61.37	42.48	23.82	6.87	5.63	4.09	3.40	2.89	3.84
2	81.56	61.12	42.15	22.64	5.95	3.18	1.90	1.28	0.80	0.20
3	81.15	60.67	41.99	22.65	5.86	3.07	1.64	1.41	0.79	0.20
4	82.47	61.06	42.63	23.38	6.78	4.85	2.77	2.25	1.87	0.83
Hi ΔSIR	86.58	61.22	41.89	23.48	7.01	11.90	7.32	7.12	6.60	6.27

Table E.2, continued:

	Panel G: Book-to-market					Panel H: Idiosyncratic volatility				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	28.33	30.45	29.24	28.64	19.50	1.83	1.80	1.93	2.38	2.98
2	30.11	34.69	38.46	40.03	40.27	1.64	1.62	1.86	2.39	3.22
3	31.26	34.82	38.49	39.36	21.03	1.63	1.59	1.89	2.41	3.39
4	29.99	33.65	35.26	33.59	30.09	1.74	1.70	1.87	2.45	3.25
Hi ΔSIR	28.64	30.08	27.16	22.78	19.59	2.02	2.03	2.28	2.75	3.54

	Panel I: SIRIO					Panel J: Option Volatility Spread				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	6.19	6.27	8.06	13.64	78.15	-0.92	-0.83	-0.97	-1.22	-2.91
2	3.51	2.82	2.77	3.01	9.54	-0.67	-0.56	-0.71	-1.04	-0.61
3	3.44	2.49	2.80	2.79	11.92	-0.70	-0.61	-0.37	-1.69	-1.00
4	5.50	4.32	4.96	7.47	38.28	-0.59	-0.49	-0.85	-0.67	-1.08
Hi ΔSIR	13.23	12.13	18.46	36.10	170.22	-1.12	-1.17	-1.54	-2.18	-4.18

	Panel K: Analyst Earnings Forecast Dispersion				
	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	7.52	7.47	9.48	11.12	14.37
2	6.15	6.13	7.53	11.42	14.77
3	5.66	5.89	8.57	10.87	14.52
4	6.74	5.91	8.09	12.55	10.54
Hi ΔSIR	8.53	8.45	11.30	16.89	19.80

Table E.3: Explaining the returns from conditional sort with conventional factors. We regress monthly returns to a portfolio going short low institutional ownership, high change in short-interest winners and long all other winner portfolios ("Betting Against Winners" (BAW), Panel A) on different long-short portfolio returns. Panel B repeats the exercise with the excess-return of the short-side of the BAW portfolio and Panel C uses the low IOR, high change in short-interest losers as the left-hand-side portfolio. Column (1) shows the raw average of that strategy, column (2) displays results from a CAPM regression on the market excess return. Column (3) represents results from a Fama and French (1993) 3-factor regression. In column (4), we add the Carhart (1997) momentum-factor, and in column (5), IVOL as in Ang, Hodrick, Xing, and Zhang (2006) is included. Columns (6), (7) and (8) add the Pastor and Stambaugh (2003) liquidity factor, a short-term reversal portfolio and the CME factor based on short interest over institutional ownership from Drechsler and Drechsler (2016), respectively. Column (9) includes all of the aforementioned. Newey and West (1987) t-statistics are shown in parentheses.

Panel A: Excess returns of the "Betting Against Winners" portfolio

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	1.46	1.67	1.65	1.56	1.42	1.59	1.59	0.85	0.88
	(3.80)	(4.35)	(4.45)	(4.17)	(3.87)	(4.12)	(4.29)	(2.45)	(2.43)
MktRF		-0.34	-0.23	-0.20	-0.14	-0.20	-0.16	-0.02	0.01
		(-3.44)	(-2.68)	(-2.16)	(-1.53)	(-1.97)	(-1.58)	(-0.27)	(0.17)
HML			0.16	0.18	0.07	0.17	0.18	-0.18	-0.20
			(1.05)	(1.05)	(0.52)	(1.05)	(1.11)	(-1.18)	(-1.12)
SMB			-0.57	-0.57	-0.37	-0.58	-0.56	-0.29	-0.22
			(-4.63)	(-4.00)	(-2.26)	(-4.37)	(-3.86)	(-1.81)	(-1.15)
WML				0.04	0.00	0.04	0.03	-0.01	-0.03
				(0.88)	(0.01)	(0.90)	(0.66)	(-0.39)	(-0.74)
IVOL					-0.13				-0.06
					(-2.03)				(-0.92)
LIQ						-0.06			-0.05
						(-0.49)			(-0.42)
REV							-0.20		-0.13
							(-1.49)		(-1.07)
CME								0.53	0.49
								(4.46)	(4.36)

Table E.3, continued:

Panel B: Excess returns of low institutional ownership, high change in short-interest winners

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.56	-1.45	-1.41	-1.73	-1.47	-1.74	-1.76	-0.94	-0.93
	(-1.10)	(-3.06)	(-3.52)	(-4.28)	(-4.09)	(-4.38)	(-4.48)	(-2.76)	(-2.76)
MktRF		1.39	1.17	1.29	1.19	1.29	1.24	1.09	1.02
		(9.83)	(11.60)	(12.57)	(12.75)	(13.41)	(12.93)	(13.32)	(12.48)
HML			-0.30	-0.23	-0.04	-0.23	-0.24	0.17	0.23
			(-1.40)	(-1.23)	(-0.23)	(-1.12)	(-1.13)	(1.00)	(1.19)
SMB			1.25	1.23	0.85	1.24	1.22	0.91	0.70
			(7.15)	(9.00)	(4.64)	(8.08)	(8.01)	(5.95)	(3.93)
WML				0.15	0.22	0.14	0.16	0.21	0.25
				(3.24)	(4.89)	(3.13)	(3.52)	(4.54)	(5.11)
IVOL					0.24				0.17
					(3.23)				(2.65)
LIQ						0.03			0.02
						(0.22)			(0.15)
REV							0.24		0.17
							(1.33)		(1.27)
CME								-0.59	-0.48
								(-4.80)	(-4.28)

Panel C: Excess returns of low institutional ownership, high change in short-interest losers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.56	-1.45	-1.41	-1.73	-1.47	-1.74	-1.76	-0.94	-0.93
	(-1.10)	(-3.06)	(-3.52)	(-4.28)	(-4.09)	(-4.38)	(-4.48)	(-2.76)	(-2.76)
MktRF		1.39	1.17	1.29	1.19	1.29	1.24	1.09	1.02
		(9.83)	(11.60)	(12.57)	(12.75)	(13.41)	(12.93)	(13.32)	(12.48)
HML			-0.30	-0.23	-0.04	-0.23	-0.24	0.17	0.23
			(-1.40)	(-1.23)	(-0.23)	(-1.12)	(-1.13)	(1.00)	(1.19)
SMB			1.25	1.23	0.85	1.24	1.22	0.91	0.70
			(7.15)	(9.00)	(4.64)	(8.08)	(8.01)	(5.95)	(3.93)
WML				0.15	0.22	0.14	0.16	0.21	0.25
				(3.24)	(4.89)	(3.13)	(3.52)	(4.54)	(5.11)
IVOL					0.24				0.17
					(3.23)				(2.65)
LIQ						0.03			0.02
						(0.22)			(0.15)
REV							0.24		0.17
							(1.33)		(1.27)
CME								-0.59	-0.48
								(-4.80)	(-4.28)

Table E.4: Excess returns of winner portfolios from 5x3x3 sort: This table contains monthly average excess returns of the 9 winner portfolios from a triple sort on the past 11-month return lagged by one month (quintiles), institutional ownership (terciles) and change in short interest over the past year (terciles). The second to last column presents the difference of low and high institutional ownership portfolios and the last column displays the alpha of that difference portfolio from a Fama-French three-factor regression. Similarly, the bottom two rows show the difference between high and low change in short-interest portfolios and the respective Fama-French three-factor alpha. Newey and West (1987) t-statistics are shown in parentheses.

	Hi IOR	2	Lo IOR	Lo–Hi	FF3-a
Lo ΔSIR	0.98	0.84	1.15	0.17 (0.53)	0.14 (0.46)
2	0.96	0.89	0.65	-0.30 (-0.97)	-0.25 (-0.86)
Hi ΔSIR	0.99	0.98	0.04	-0.95 (-3.11)	-1.01 (-3.18)
Hi–Lo	0.01	0.14	-1.11		
t	(0.10)	(0.50)	(-2.89)		
FF3-a	-0.04	0.13	-1.18		
t	(-0.25)	(0.45)	(-2.88)		

Table E.5: Characteristics of triple sorted winner portfolios from 5x3x3 sort: This table shows time-series averages of value-weighted mean characteristics of the 9 winner portfolios from a 5x3x3 sort in the month of portfolio formation. Panel A displays the average number of stocks. Following are average market equity in billion US dollars (Panel B), return from month t-12 to the end of month t-2 in percent (Panel C), change in short interest from 11.5 months ago to 2 weeks ago in percentage points (Panel D), institutional ownership in percent of number of shares outstanding (Panel E), level of short interest prior to portfolio formation (Panel F), the ratio of book equity of the previous December to last month's market equity in percent (Panel G) and the previous month's idiosyncratic volatility as in Ang et al. (2006) in percent (Panel H).

	Panel A: Number of Stocks			Panel B: Average Market Equity		
	Hi IOR	2	Lo IOR	Hi IOR	2	Lo IOR
Lo ΔSIR	117	92	66	22.83	50.63	15.13
2	56	90	128	31.45	55.13	14.11
Hi ΔSIR	123	92	60	15.53	32.39	4.36

	Panel C: Formation Period Return			Panel D: Change in Short-Interest		
	Hi IOR	2	Lo IOR	Hi IOR	2	Lo IOR
Lo ΔSIR	76.77	86.72	107.22	-2.76	-2.51	-3.58
2	70.44	77.01	103.08	0.13	0.11	0.08
Hi ΔSIR	82.87	99.51	156.58	2.84	2.48	4.16

	Panel E: Institutional Ownership			Panel F: Level of Short-interest		
	Hi IOR	2	Lo IOR	Hi IOR	2	Lo IOR
Lo ΔSIR	75.30	45.29	15.56	3.54	2.82	2.97
2	72.75	44.40	14.50	2.14	1.26	0.78
Hi ΔSIR	77.27	44.45	15.06	6.39	4.89	5.95

	Panel G: Book-to-market			Panel H: Idiosyncratic volatility		
	Hi IOR	2	Lo IOR	Hi IOR	2	Lo IOR
Lo ΔSIR	30.57	30.38	28.24	1.68	1.79	2.57
2	32.93	36.45	29.86	1.55	1.74	2.64
Hi ΔSIR	30.36	29.29	22.65	1.78	2.00	2.98

Table E.5, continued:

	Panel I: SIRIO			Panel J: Option Volatility Spread		
	Hi IOR	2	Lo IOR	Hi IOR	2	Lo IOR
Lo ΔSIR	4.31	6.37	37.70	-0.70	-0.73	-1.92
2	2.68	2.66	9.91	-0.65	-0.67	-0.92
Hi ΔSIR	7.76	12.62	85.63	-0.79	-0.98	-2.34

	Panel K: Analyst Earnings Forecast Dispersion		
	Hi IOR	2	Lo IOR
Lo ΔSIR	6.39	7.87	11.20
2	5.43	7.35	10.18
Hi ΔSIR	7.07	9.09	17.58

Table E.6: Explaining the returns from 5x3x3 sort with conventional factors: We regress monthly returns to a portfolio going short low institutional ownership, high change in short-interest winners and long all other winner portfolios ("Betting Against Winners" (BAW), Panel A) on different long-short portfolio returns. Panel B repeats the exercise with the excess-return of the short-side of the BAW portfolio and Panel C uses the low IOR, high change in short-interest losers as the left-hand-side portfolio. Column (1) shows the raw average of that strategy, column (2) displays results from a CAPM regression on the market excess return. Column (3) represents results from a Fama and French (1993) 3-factor regression. In column (4), we add the Carhart (1997) momentum-factor, and in column (5), IVOL as in Ang, Hodrick, Xing, and Zhang (2006) is included. Columns (6), (7) and (8) add the Pastor and Stambaugh (2003) liquidity factor, a short-term reversal portfolio and the CME factor based on short interest over institutional ownership from Drechsler and Drechsler (2016), respectively. Column (9) includes all of the aforementioned. Newey and West (1987) t-statistics are shown in parentheses.

Panel A: Excess returns of the "Betting Against Winners" portfolio									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.89	1.08	1.01	0.96	0.98	0.96	0.98	0.69	0.74
	(3.17)	(3.50)	(3.65)	(3.71)	(3.73)	(3.58)	(3.60)	(2.35)	(2.37)
MktRF		-0.31	-0.17	-0.15	-0.16	-0.15	-0.12	-0.09	-0.08
		(-2.78)	(-1.87)	(-1.73)	(-1.86)	(-1.70)	(-1.31)	(-0.87)	(-0.81)
HML			0.32	0.34	0.35	0.33	0.34	0.20	0.24
			(2.49)	(2.60)	(2.65)	(2.57)	(2.67)	(1.31)	(1.48)
SMB			-0.57	-0.57	-0.61	-0.57	-0.56	-0.46	-0.54
			(-4.57)	(-4.53)	(-4.54)	(-4.57)	(-4.65)	(-3.11)	(-3.66)
WML				0.02	0.03	0.02	0.01	0.00	0.01
				(0.80)	(0.97)	(0.79)	(0.40)	(0.06)	(0.23)
IVOL					0.03				0.06
					(0.55)				(1.19)
LIQ						-0.00			0.02
						(-0.01)			(0.21)
REV							-0.18		-0.15
							(-1.64)		(-1.17)
CME								0.20	0.22
								(2.14)	(1.94)

Table E.6, continued:

Panel B: Excess returns of low institutional ownership, high change in short-interest winners									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.04	-0.81	-0.70	-1.06	-0.98	-1.05	-1.09	-0.71	-0.73
	(0.12)	(-2.25)	(-2.68)	(-3.84)	(-3.67)	(-3.84)	(-3.74)	(-2.44)	(-2.41)
MktRF		1.33	1.09	1.23	1.20	1.23	1.18	1.14	1.10
		(9.05)	(10.32)	(13.95)	(13.18)	(13.55)	(13.34)	(12.66)	(11.99)
HML			-0.47	-0.40	-0.34	-0.40	-0.40	-0.22	-0.23
			(-2.47)	(-2.63)	(-2.23)	(-2.59)	(-2.57)	(-1.41)	(-1.34)
SMB			1.12	1.10	0.99	1.10	1.09	0.96	0.91
			(7.26)	(8.60)	(8.35)	(8.54)	(8.27)	(6.98)	(6.82)
WML				0.16	0.19	0.17	0.18	0.19	0.21
				(5.00)	(4.55)	(5.02)	(4.24)	(5.40)	(4.14)
IVOL					0.07				0.04
					(1.34)				(0.69)
LIQ						-0.03			-0.05
						(-0.34)			(-0.65)
REV							0.23		0.21
							(1.72)		(1.55)
CME								-0.26	-0.22
								(-3.00)	(-2.35)

Panel C: Excess returns of low institutional ownership, high change in short-interest losers									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-1.05	-1.98	-2.09	-1.02	-0.52	-1.03	-1.03	0.15	0.27
	(-1.63)	(-4.10)	(-4.90)	(-2.15)	(-0.96)	(-2.36)	(-2.21)	(0.28)	(0.47)
MktRF		1.47	1.31	0.91	0.71	0.91	0.89	0.62	0.53
		(8.86)	(8.69)	(8.42)	(5.76)	(8.04)	(6.00)	(4.49)	(3.29)
HML			0.17	-0.06	0.31	-0.06	-0.07	0.53	0.69
			(0.56)	(-0.29)	(1.65)	(-0.30)	(-0.29)	(5.48)	(3.41)
SMB			1.25	1.30	0.56	1.30	1.30	0.83	0.36
			(5.39)	(9.21)	(2.78)	(9.17)	(9.44)	(5.20)	(1.65)
WML				-0.49	-0.35	-0.49	-0.49	-0.40	-0.32
				(-5.42)	(-4.29)	(-5.24)	(-5.85)	(-6.42)	(-5.08)
IVOL					0.47				0.36
					(5.28)				(3.77)
LIQ						0.02			0.04
						(0.12)			(0.34)
REV							0.07		-0.04
							(0.25)		(-0.18)
CME								-0.88	-0.69
								(-4.34)	(-3.32)

Table E.7: Excess returns of winner portfolios when excluding the 20% smallest stocks: This table contains monthly average excess returns of the 25 winner portfolios from a triple sort on the past 11-month return lagged by one month, institutional ownership and change in short interest over the past year. The 20% smallest stocks in each month are excluded from the analysis. The second to last column presents the difference of low and high institutional ownership portfolios and the last column displays the alpha of that difference portfolio from a Fama-French three-factor regression. Similarly, the bottom two rows show the difference between high and low change in short-interest portfolios and the respective Fama-French three-factor alpha. Newey and West (1987) t-statistics are shown in parentheses.

	Hi IOR	4	3	2	Lo IOR	Lo–Hi	FF3-a
Lo ΔSIR	1.34	0.93	1.49	1.12	1.03	-0.30 (-0.51)	-0.23 (-0.35)
2	1.10	0.70	0.97	1.03	1.14	0.04 (0.08)	0.02 (0.06)
3	1.28	1.18	0.87	0.85	0.57	-0.71 (-1.80)	-0.69 (-1.97)
4	0.98	1.25	0.88	0.94	0.29	-0.69 (-2.09)	-0.74 (-2.20)
Hi ΔSIR	1.11	1.03	0.93	1.10	-0.78	-1.89 (-4.27)	-1.84 (-4.54)
Hi–Lo	-0.23	0.10	-0.57	-0.01	-1.82		
t	(-0.86)	(0.31)	(-1.45)	(-0.03)	(-2.55)		
FF3-a	-0.39	0.01	-0.63	-0.15	-2.00		
t	(-1.47)	(0.04)	(-1.51)	(-0.28)	(-2.93)		

Table E.8: Characteristics of triple sorted winner portfolios when excluding the 20% smallest stocks: This table shows time-series averages of value-weighted mean characteristics of the 25 winner portfolios in the month of portfolio formation. The 20% smallest stocks in each month are excluded from the analysis. Panel A displays the average number of stocks. Following are average market equity in billion US dollars (Panel B), return from month t-12 to the end of month t-2 in percent (Panel C), change in short interest from 11.5 months ago to 2 weeks ago in percentage points (Panel D), institutional ownership in percent of number of shares outstanding (Panel E), level of short interest prior to portfolio formation (Panel F), the ratio of book equity of the previous December to last month's market equity in percent (Panel G) and the previous month's idiosyncratic volatility as in Ang, Hodrick, Xing, and Zhang (2006) in percent (Panel H).

	Panel A: Number of Stocks					Panel B: Average Market Equity				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	39	34	25	19	13	10.99	19.53	29.82	22.46	7.07
2	20	25	27	29	29	14.43	30.98	40.69	20.90	5.21
3	16	23	28	32	31	11.51	30.85	37.11	26.02	7.96
4	28	30	28	24	19	11.96	25.92	28.03	14.63	2.91
Hi ΔSIR	41	29	24	22	15	7.10	9.74	13.35	9.83	2.60

	Panel C: Formation Period Return					Panel D: Change in Short-Interest				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	83.53	89.15	101.61	116.97	124.79	-4.29	-4.10	-4.37	-4.25	-8.84
2	73.13	76.05	78.60	88.99	103.08	-0.56	-0.53	-0.52	-0.50	-0.46
3	76.73	77.36	82.25	89.76	110.26	0.11	0.11	0.09	0.08	0.07
4	77.47	80.57	89.87	110.15	133.36	0.95	0.88	0.89	0.87	0.88
Hi ΔSIR	90.74	103.02	118.51	146.30	180.10	5.21	4.29	4.59	5.11	6.56

	Panel E: Institutional Ownership					Panel F: Level of Short-interest				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	84.49	64.70	48.19	30.80	11.89	5.21	3.71	4.19	3.66	5.05
2	82.89	64.23	47.71	30.41	11.50	3.17	1.84	1.49	1.42	1.13
3	83.32	64.25	47.88	30.75	12.02	3.01	1.75	1.40	1.19	0.82
4	83.79	64.57	47.84	30.82	11.78	4.21	2.99	2.69	2.51	2.03
Hi ΔSIR	87.12	64.85	47.72	30.35	11.89	10.35	8.03	7.98	7.96	8.86

Table E.8, continued:

	Panel G: Book-to-market					Panel H: Idiosyncratic volatility				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	27.76	30.25	27.93	27.57	22.25	1.82	1.78	1.94	2.29	2.83
2	31.73	36.12	35.12	38.62	29.19	1.65	1.64	1.79	2.10	2.69
3	32.12	35.02	36.67	37.45	22.05	1.66	1.65	1.81	2.13	2.67
4	29.52	32.11	33.25	29.29	22.82	1.72	1.69	1.85	2.29	2.97
Hi ΔSIR	28.73	29.28	28.25	24.11	17.10	1.97	2.05	2.32	2.68	3.34

	Panel I: SIRIO					Panel J: Option Volatility Spread				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	5.61	5.39	8.27	13.58	75.11	-0.89	-0.84	-0.93	-1.39	-1.46
2	3.43	2.61	2.82	4.26	29.15	-0.68	-0.62	-0.63	-0.94	-2.73
3	3.26	2.46	2.63	3.36	11.00	-0.66	-0.67	-0.63	-0.98	-1.18
4	4.64	4.29	5.31	8.32	46.83	-0.63	-0.57	-0.84	-0.80	-0.16
Hi ΔSIR	11.33	12.19	17.86	34.57	154.13	-0.96	-1.14	-1.34	-2.05	-4.07

	Panel K: Analyst Earnings Forecast Dispersion				
	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	7.43	7.61	9.18	13.70	13.83
2	6.20	6.43	7.32	9.48	12.51
3	6.05	5.92	7.80	9.72	11.62
4	6.66	5.75	7.88	11.97	15.23
Hi ΔSIR	8.48	8.40	11.28	14.31	20.84

Table E.9: Explaining the returns with conventional factors excluding the 20% smallest stocks: We regress monthly returns to a portfolio going short low institutional ownership, high change in short-interest winners and long all other winner portfolios ("Betting Against Winners" (BAW), Panel A), disregarding the 20% smallest stocks, on different long-short portfolio returns. Panel B repeats the exercise with the excess-return of the short-side of the BAW portfolio and Panel C uses the low IOR, high change in short-interest losers as the left-hand-side portfolio. Column (1) shows the raw average of that strategy, column (2) displays results from a CAPM regression on the market excess return. Column (3) represents results from a Fama and French (1993) 3-factor regression. In column (4), we add the Carhart (1997) momentum-factor, and in column (5), IVOL as in Ang, Hodrick, Xing, and Zhang (2006) is included. Columns (6), (7) and (8) add the Pastor and Stambaugh (2003) liquidity factor, a short-term reversal portfolio and the CME factor based on short interest over institutional ownership from Drechsler and Drechsler (2016), respectively. Column (9) includes all of the aforementioned. Newey and West (1987) t-statistics are shown in parentheses.

Panel A: Excess returns of the "Betting Against Winners" portfolio

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	1.78	1.98	1.86	1.77	1.65	1.75	1.78	1.04	1.06
	(4.29)	(4.52)	(4.62)	(4.34)	(4.12)	(4.09)	(4.38)	(2.62)	(2.54)
MktRF		-0.30	-0.17	-0.14	-0.08	-0.14	-0.12	0.12	0.11
		(-2.15)	(-1.49)	(-1.28)	(-0.60)	(-1.32)	(-1.03)	(0.99)	(0.88)
HML			0.42	0.44	0.35	0.45	0.45	-0.11	-0.08
			(2.35)	(2.58)	(2.11)	(2.63)	(3.06)	(-0.54)	(-0.40)
SMB			-0.40	-0.41	-0.23	-0.41	-0.40	0.02	-0.04
			(-2.74)	(-2.74)	(-1.31)	(-2.77)	(-3.10)	(0.13)	(-0.22)
WML				0.04	0.01	0.04	0.04	-0.04	-0.03
				(1.23)	(0.25)	(1.19)	(0.83)	(-0.91)	(-0.68)
IVOL					-0.12				0.06
					(-1.57)				(0.67)
LIQ						0.03			0.02
						(0.22)			(0.19)
REV							-0.10		-0.05
							(-0.67)		(-0.30)
CME								0.72	0.75
								(5.37)	(4.69)

Table E.9, continued:

Panel B: Excess returns of low institutional ownership, high change in short-interest winners									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.78	-1.68	-1.53	-1.94	-1.69	-1.93	-1.97	-1.13	-1.12
	(-1.39)	(-3.37)	(-3.76)	(-4.85)	(-4.25)	(-4.59)	(-4.83)	(-3.09)	(-2.84)
MktRF		1.40	1.14	1.28	1.14	1.28	1.25	0.99	0.94
		(8.39)	(9.90)	(10.63)	(9.05)	(11.70)	(10.93)	(9.71)	(7.94)
HML			-0.63	-0.51	-0.30	-0.51	-0.51	0.11	0.12
			(-3.02)	(-2.67)	(-1.76)	(-3.13)	(-2.51)	(0.53)	(0.57)
SMB			1.12	1.09	0.71	1.09	1.07	0.61	0.51
			(5.83)	(6.81)	(3.86)	(7.66)	(6.60)	(3.53)	(2.90)
WML				0.19	0.26	0.19	0.20	0.29	0.31
				(4.37)	(4.73)	(4.23)	(4.29)	(5.31)	(5.61)
IVOL					0.25				0.08
					(2.99)				(1.00)
LIQ						-0.03			-0.03
						(-0.29)			(-0.21)
REV							0.17		0.13
							(0.91)		(0.80)
CME								-0.80	-0.74
								(-6.58)	(-5.09)

Panel C: Excess returns of low institutional ownership, high change in short-interest losers									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-1.51	-2.52	-2.52	-1.40	-1.11	-1.45	-1.40	-0.42	-0.45
	(-1.86)	(-3.65)	(-3.80)	(-2.31)	(-1.59)	(-2.21)	(-2.24)	(-0.67)	(-0.61)
MktRF		1.58	1.37	0.99	0.83	0.99	0.98	0.64	0.62
		(9.26)	(8.72)	(8.70)	(5.79)	(8.00)	(7.22)	(3.92)	(3.46)
HML			-0.14	-0.47	-0.24	-0.46	-0.47	0.27	0.32
			(-0.50)	(-1.97)	(-0.93)	(-1.96)	(-1.98)	(0.86)	(0.94)
SMB			1.27	1.35	0.92	1.36	1.35	0.77	0.70
			(3.96)	(5.64)	(2.78)	(4.91)	(5.57)	(3.22)	(1.99)
WML				-0.51	-0.44	-0.52	-0.51	-0.40	-0.39
				(-8.11)	(-6.09)	(-7.76)	(-8.59)	(-6.90)	(-5.28)
IVOL					0.28				0.07
					(2.44)				(0.62)
LIQ						0.10			0.13
						(0.55)			(0.72)
REV							0.02		-0.07
							(0.10)		(-0.28)
CME								-0.96	-0.93
								(-4.24)	(-3.64)

F Additional Data Cleaning

We identify some issues with the short interest data as well as the institutional ownership data. These issues shrink our sample and induce additional noise, which should strictly weaken our results. First, suppose a firm is identified as having a high change in short interest but really had no change in short interest. We might include this firm in the constrained winner portfolio, while it really is not constrained. If the firm displays "regular" returns, it will bias the results of the portfolio towards a too high return. Second, we increase our sample size and thus the pool of potentially constrained firms, which again should reduce noise. The short interest data come from four different sources. Compustat is available from 1973, but only starts NASDAQ coverage from July 2003. We have additional files from each exchange, NYSE (1988/01 – 2005/07), AMEX (1995/01 – 2005/07) and NASDAQ (1988/06 – 2008/07, except February and July of 1990). One file typically covers one month of data for one exchange. The format varies widely – most files have tickers, some do not. Tickers typically have the share class appended at the end. In CRSP, the share class is sometimes included in the ticker and sometimes it is not. Ordinary matching on tickers misses some stocks with multiple share classes and all files that do not include tickers. We thus apply the following procedure to improve matching:

- Within each file we identify issues of the same company by name matching.
- We identify the share class from the name or the ticker within multiple issue companies.
- We match by ticker where uniquely possible.
- We match by ticker and share class where uniquely possible.
- We match the remaining firms by name and share class.

The name matching procedure for identifying multiple issues within files and for matching CRSP names with short interest file names first standardizes names by removing unnecessary whitespaces and punctuation, harmonizing abbreviations and acronyms and removing additional information (like "Class A" or "Incorporated"). We then calculate the Levenshtein distance to assess name similarity. We discount common words like "American" and put more weight on the unique part of company names. Additionally, we allow for word rotation.

In the current version of the paper we have 1,488,655 firm month observations with short interest. After applying the procedure above and allowing for firms from all four sources within any given month, we end up with 1,704,806 firm month observations, a 15% increase, 2/3 of which come from the new matching and 1/3 comes from allowing all sources within a month. Our short interest data now covers 87% of all observations in CRSP in our sample period.

The results of our main analyses get strictly stronger. The Sharpe ratio of the BAW portfolio increases from 1.08 to 1.19. The portfolio now contains 21 instead of 16 stocks per month, on average.

There are also some apparent issues with institutional ownership data, which have recently been confirmed by WRDS.[26] We identify a few cases where institutional ownership decreases in one quarter by more than 50pp and increases by more than 50pp in the next quarter again. For example, Halliburton's institutional ownership falls from 83% to 0.2% in 06/2008 and is back at a level of 79% in the following quarter again. Thereby, Halliburton ends up in the corner portfolio in one month, while it is highly unlikely that it was actually short-sale constrained.

We fix this issue by setting institutional ownership to the previous observation if we observe an extreme decrease of more than 50pp that fully reverses in the following quarter. This happens 115 times in the sample – but even very few observations like Halliburton can have an influence on value weighted portfolio returns. This fix further increases the Sharpe ratio of BAW to 1.22.

Tables F.1 to F.3 provide results based on the updated data, i.e., including the improvements in data quality for short interest and institutional ownership. As can be seen, the main effects become stronger.

[26] See the note issued by WRDS on March 6, 2017, concerning "Data Quality problems in Thomson Reuters Ownership."

Table F.1: Excess returns of winner and loser portfolios with improved SIR and IOR data. This table contains monthly average excess returns of the 25 winner (Panel A) and 25 loser (Panel B) portfolios from a triple sort on the past 11-month return lagged by one month, institutional ownership and change in short interest over the past year. The second to last column presents the difference of low and high institutional ownership portfolios and the last column displays the alpha of that difference portfolio from a Fama-French three-factor regression. Similarly, the bottom two rows show the difference between high and low change in short-interest portfolios and the respective Fama-French three-factor alpha. Newey and West (1987) t-statistics are shown in parentheses. The difference to Table 3 in the main paper is that we apply the techniques described in Appendix F to improve the quality of short interest and institutional ownership data.

Panel A: Winners

	Hi IOR	4	3	2	Lo IOR	Lo–Hi	FF3-a
Lo ΔSIR	0.90	0.77	1.42	1.17	1.32	0.44 (0.74)	0.29 (0.53)
2	1.06	1.01	0.85	1.50	0.73	-0.33 (-0.73)	-0.29 (-0.65)
3	1.20	1.19	0.87	0.89	1.05	-0.15 (-0.47)	-0.06 (-0.20)
4	1.02	0.87	0.70	0.62	0.30	-0.73 (-2.34)	-0.74 (-1.88)
Hi ΔSIR	0.95	0.77	0.91	0.05	-1.75	-2.70 (-6.21)	-2.69 (-5.95)
Hi–Lo	0.05	0.00	-0.52	-1.12	-3.09		
t	(0.23)	(0.01)	(-1.13)	(-2.35)	(-4.56)		
FF3-a	-0.08	-0.12	-0.73	-1.22	-3.06		
t	(-0.38)	(-0.37)	(-1.64)	(-2.47)	(-4.80)		

Panel B: Losers

	Hi IOR	4	3	2	Lo IOR	Lo–Hi	FF3-a
Lo ΔSIR	0.39	0.18	-0.31	-0.69	-1.64	-2.04 (-3.31)	-1.67 (-2.49)
2	0.76	0.79	0.35	-0.38	-1.34	-2.10 (-2.87)	-1.63 (-2.27)
3	-0.30	0.47	0.50	0.17	0.27	0.57 (1.15)	0.99 (1.86)
4	0.07	0.27	0.32	-0.33	-0.77	-0.84 (-1.37)	-0.63 (-1.07)
Hi ΔSIR	-0.18	-0.53	-0.73	-1.82	-2.18	-2.10 (-2.71)	-2.12 (-2.63)
Hi–Lo	-0.57	-0.71	-0.42	-1.13	-0.61		
t	(-1.54)	(-1.71)	(-1.05)	(-1.53)	(-0.72)		
FF3-a	-0.42	-0.74	-0.69	-1.19	-0.84		
t	(-1.14)	(-1.97)	(-1.65)	(-2.02)	(-1.05)		

Table F.2: Characteristics of triple sorted winner portfolios with improved SIR and IOR data. This table shows time-series averages of value-weighted mean characteristics of the 25 winner portfolios in the month of portfolio formation. Panel A displays the average number of stocks. Following are average market equity in billion US dollars (Panel B), return from month t-12 to the end of month t-2 in percent (Panel C), change in short interest from 11.5 months ago to 2 weeks ago in percentage points (Panel D), institutional ownership in percent of number of shares outstanding (Panel E), level of short interest prior to portfolio formation (Panel F), the ratio of book equity of the previous December to last month's market equity in percent (Panel G) and the previous month's idiosyncratic volatility as in Ang, Hodrick, Xing, and Zhang (2006) in percent (Panel H). The difference to Table 4 in the main paper is that we apply the techniques described in Appendix F to improve the quality of short interest and institutional ownership data.

	Panel A: Number of Stocks					Panel B: Average Market Equity				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	58	49	37	26	18	13.35	23.26	27.11	7.21	3.45
2	20	29	36	45	53	13.92	36.06	46.77	22.84	3.37
3	18	28	37	48	58	13.86	37.19	44.56	20.25	5.50
4	38	43	41	35	31	13.91	28.80	28.25	10.24	2.01
Hi ΔSIR	61	42	36	29	21	7.58	9.07	8.26	3.95	0.97

	Panel C: Formation Period Return					Panel D: Change in Short-Interest				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	81.75	84.59	95.04	110.99	114.08	-2.98	-2.56	-2.49	-2.35	-2.40
2	73.10	69.30	76.62	87.06	96.29	-0.33	-0.32	-0.32	-0.28	-0.26
3	76.68	73.11	79.03	89.07	105.60	0.14	0.12	0.12	0.12	0.11
4	76.78	79.68	90.29	113.53	145.30	0.87	0.80	0.81	0.81	0.78
Hi ΔSIR	93.47	108.33	126.01	161.38	191.41	4.30	3.70	3.99	4.34	4.28

	Panel E: Institutional Ownership					Panel F: Level of Short-interest				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	80.44	61.29	43.17	24.10	6.80	4.10	2.70	2.60	2.70	1.62
2	79.32	60.58	42.51	23.26	6.36	2.72	1.51	1.16	1.00	0.61
3	79.44	60.23	42.03	23.18	7.43	2.73	1.61	1.21	0.99	0.54
4	79.82	60.81	42.58	23.66	7.20	3.60	2.61	2.26	2.01	1.63
Hi ΔSIR	82.62	60.92	42.11	24.00	7.04	8.41	6.56	6.45	6.71	5.72

Table F.2, continued:

	Panel G: Book-to-market					Panel H: Idiosyncratic volatility				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	28.13	32.57	30.99	27.63	25.22	1.81	1.74	1.95	2.46	3.12
2	31.98	36.87	38.17	39.62	35.37	1.68	1.59	1.80	2.31	2.97
3	30.04	35.68	38.63	40.08	33.57	1.66	1.62	1.86	2.24	2.86
4	29.82	32.99	33.67	28.47	20.72	1.70	1.70	1.93	2.48	3.35
Hi ΔSIR	28.44	29.12	26.05	21.59	6.91	1.99	2.14	2.45	3.01	3.86

	Panel I: SIRIO					Panel J: Option Volatility Spread				
	Hi IOR	4	3	2	Lo IOR	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	4.71	4.29	6.23	12.92	79.49	-0.83	-0.86	-0.90	-1.47	-2.04
2	3.11	2.25	2.39	3.73	22.77	-0.82	-0.49	-0.54	-1.42	-2.48
3	3.13	2.40	2.50	3.55	17.14	-0.72	-0.61	-0.58	-0.83	-0.87
4	4.17	3.98	5.05	8.80	70.00	-0.65	-0.58	-0.67	-0.70	-1.47
Hi ΔSIR	9.68	10.71	16.58	37.99	201.91	-1.04	-1.23	-1.85	-3.03	-6.18

	Panel K: Analyst Earnings Forecast Dispersion				
	Hi IOR	4	3	2	Lo IOR
Lo ΔSIR	8.98	8.57	12.38	16.41	27.82
2	6.65	7.09	7.78	12.34	19.79
3	6.76	6.48	9.60	10.49	13.51
4	7.47	6.61	9.56	16.93	16.77
Hi ΔSIR	10.14	11.08	15.22	22.22	31.65

Table F.3: Explaining the returns with conventional factors with improved SIR and IOR data: We regress monthly returns to a portfolio going short low institutional ownership, high change in short-interest winners and long all other winner portfolios ("Betting Against Winners", BAW, Panel A) on different long-short portfolio returns. Panel B repeats the exercise with the excess-return of the short-side of the BAW portfolio and Panel C uses the low IOR, high change in short-interest losers as the left-hand-side portfolio. Column (1) shows the raw average of that strategy, column (2) displays results from a CAPM regression on the market excess return. Column (3) represents results from a Fama and French (1993) 3-factor regression. In column (4), we add the Carhart (1997) momentum-factor, and in column (5), IVOL as in Ang, Hodrick, Xing, and Zhang (2006) is included. Columns (6), (7) and (8) add the Pastor and Stambaugh (2003) liquidity factor, a short-term reversal portfolio and the CME factor based on short interest over institutional ownership from Drechsler and Drechsler (2016), respectively. Column (9) includes all of the aforementioned. Newey and West (1987) t-statistics are shown in parentheses.

Panel A: Excess returns of the "Betting Against Winners" portfolio

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	2.67	2.80	2.74	2.66	2.56	2.73	2.71	1.83	2.01
	(6.70)	(6.68)	(6.52)	(6.52)	(6.14)	(6.42)	(6.78)	(4.71)	(3.94)
MktRF		-0.21	-0.09	-0.06	-0.02	-0.05	0.03	0.14	0.19
		(-1.90)	(-0.95)	(-0.58)	(-0.18)	(-0.48)	(0.30)	(1.49)	(1.85)
HML			0.26	0.28	0.20	0.25	0.29	-0.00	0.01
			(1.54)	(1.77)	(1.50)	(1.59)	(2.03)	(-0.00)	(0.08)
SMB			-0.53	-0.54	-0.39	-0.54	-0.50	-0.22	-0.22
			(-2.91)	(-3.25)	(-1.78)	(-3.14)	(-3.27)	(-1.15)	(-0.94)
WML				0.04	0.01	0.05	0.02	-0.03	-0.03
				(0.92)	(0.24)	(0.89)	(0.32)	(-0.57)	(-0.63)
IVOL					-0.09				-0.01
					(-1.02)				(-0.10)
LIQ						-0.18			-0.15
						(-1.49)			(-1.35)
REV							-0.41		-0.29
							(-2.57)		(-1.88)
CME								0.48	0.43
								(3.68)	(2.75)

Table F.3, continued:

Panel B: Excess returns of low institutional ownership, high change in short-interest winners									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-1.75	-2.58	-2.50	-2.81	-2.57	-2.89	-2.88	-1.75	-1.95
	(-3.99)	(-5.10)	(-5.48)	(-6.07)	(-5.97)	(-6.18)	(-7.03)	(-3.94)	(-3.46)
MktRF		1.30	1.06	1.18	1.08	1.17	1.07	0.92	0.84
		(8.66)	(9.16)	(11.54)	(9.89)	(11.88)	(10.53)	(7.93)	(7.37)
HML			-0.41	-0.34	-0.16	-0.32	-0.36	0.01	0.04
			(-2.33)	(-1.76)	(-1.11)	(-1.69)	(-2.01)	(0.05)	(0.24)
SMB			1.24	1.23	0.87	1.24	1.19	0.82	0.68
			(6.64)	(6.65)	(4.06)	(6.75)	(7.55)	(4.34)	(2.74)
WML				0.14	0.21	0.14	0.17	0.23	0.26
				(2.62)	(3.69)	(2.54)	(2.81)	(3.87)	(4.34)
IVOL					0.23				0.14
					(2.52)				(1.87)
LIQ						0.18			0.15
						(1.46)			(1.19)
REV							0.50		0.36
							(2.36)		(1.98)
CME								-0.62	-0.48
								(-4.09)	(-2.91)

Panel C: Excess returns of low institutional ownership, high change in short-interest losers									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-2.18	-3.39	-3.37	-1.98	-0.92	-2.08	-2.04	0.29	0.21
	(-2.07)	(-4.26)	(-4.05)	(-1.71)	(-0.77)	(-1.95)	(-1.89)	(0.18)	(0.14)
MktRF		1.84	1.63	1.08	0.69	1.07	0.97	0.55	0.35
		(5.64)	(6.50)	(5.26)	(2.91)	(4.42)	(3.61)	(1.92)	(1.10)
HML			-0.29	-0.60	0.14	-0.57	-0.62	0.15	0.51
			(-0.62)	(-1.67)	(0.49)	(-1.78)	(-1.61)	(0.45)	(1.54)
SMB			1.13	1.20	-0.29	1.21	1.16	0.33	-0.60
			(2.81)	(3.26)	(-0.80)	(3.26)	(3.39)	(0.78)	(-1.44)
WML				-0.67	-0.39	-0.68	-0.64	-0.48	-0.31
				(-3.15)	(-2.42)	(-3.25)	(-3.53)	(-3.99)	(-2.87)
IVOL					0.95				0.79
					(5.39)				(4.29)
LIQ						0.22			0.24
						(0.70)			(0.94)
REV							0.52		0.28
							(0.95)		(0.79)
CME								-1.32	-0.84
								(-2.62)	(-1.83)